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# Uncertainty assessment in long term urban drainage modelling

PhD Thesis  
Defended in public April 14, 2008

Søren Thorndahl

Aalborg University  
Department of Civil Engineering  
Water and Soil

**DCE Thesis No. 12**

# **Uncertainty assessment in long term urban drainage modelling**

**Defended in public April 14, 2008  
at Aalborg University**

by

Søren Thorndahl

March 2008

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## Preface

This thesis is prepared as part of a PhD study during the period November 15, 2004 to March 1 2008 at Department of Civil Engineering, Aalborg University, Denmark. The study is supervised by Associate Professor Kjeld Schaarup-Jensen and co-supervised by part-time lecturer, Msc., PhD Jacob Birk Jensen. The thesis consists of a collection of seven journal and conference papers as well as an introductive review and summery.

First of all, I would like to thank both of my supervisors, Kjeld Schaarup-Jensen and Jacob Birk Jensen, for numerous fruitful meetings and for their enthusiastic guidance throughout the study. I would like to express my gratitude to Associate Professor Michael R. Rasmussen for many discussions and his great involvement in the study. Also thanks to Professor Torben Larsen for his inputs to the project. Furthermore, I am grateful to my PhD colleague Thomas R. Bentzen with whom I have discussed and shared many professional and private matters.

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Aalborg, 1 March, 2008

Søren Thorndahl

This Thesis was defended in public at Aalborg University, April 14, 2008.

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On behalf of the Faculties of Engineering, Science and Medicine at Aalborg University the defence was chaired by Professor Torben Larsen.

## English summary

Use of hydrodynamic models, by consultants, municipalities, etc, for analysis of urban drainage systems has evolved extensively in the last decades. The models produce a detailed overview of the urban drainage systems' ability to function during rain, by predicting flooding of critical levels and overflows from combined sewer systems to receiving waters. The application of models is highly dependent on tradition and empirical assumptions concerning the choice of models, model parameters, and model inputs. In order to meet the design criteria a certain safety is often implemented in the choice of model parameter values. In some cases, this can lead to over-dimensioned sewers, causing excessive construction costs, and potentially, problems with poor self cleaning. On the other hand, however, if the necessary safeties are not implemented in the models, the sewer design will cause frequent flooding of certain areas or frequent overflows from combined sewer systems to receiving waters. Thus, from a social and an engineering point of view there is a strong need for more research in uncertainties related to both input, parameters, and predictions in urban drainage models.

Better and more reliable model results can be obtained by explaining the uncertainties and by handling them stochastically. In the end this might help reduce both construction and damage costs.

This thesis consists of initial registrations and quantifications of uncertainty contributions. Next, based on a selection of the most important uncertainties, three different stochastic methods are applied, in order to propagate the uncertainties on inputs and parameters through the model to an uncertainty estimation of the model predictions. The simulations are exemplified applying a rather small catchment in the town Frejlev, located a few kilometres from the city of Aalborg, Denmark.

The first of the applied stochastic methods is a reliability method that searches the models space for failures. In this case, failure is defined as occurrence of either surcharge or flooding of manholes or combined sewer overflow. The application implies a parameterisation of the rainfall input in order to generate synthetic Gauss-shaped rainfall events. This iterative search-algorithm has proven very applicable in locating failures in urban drainage systems because uncertainties with regards to different parameters and rainfall inputs can be included.

The second stochastic method is a Monte Carlo based stochastic calibration which applies the GLUE method (Generalized Likelihood Uncertainty Estimation). By application of flow measurements and overflow registrations in the drainage system, this method includes an event based conditioning of the model. To find the most reliable model structure, it is possible to derive the parameter distributions which contain the largest correlation between observed and simulated time series as well as to investigate different conceptual setups of



the model. The method has proven very applicable in modelling of drainage systems even though it has not been possible to bracket the observed time series completely by the predicted confidence intervals.

The last of the stochastic methods apply the results from the two previously described analyses by modelling the extreme event statistics using Monte Carlo simulations. In order to include the return period uncertainties of maximum water levels and combined sewer overflow volumes, a new methodology is proposed. This includes a derivation of correlations between input and response in the drainage system and a statistical model for characteristic rainfall parameter values as a function of the return periods. Accordingly, it has been possible to clarify the uncertainties associated with frequencies of flooding of critical levels and overflows to receiving waters. These are shown to be quite large, especially on the long return periods.

The analyses conducted in this thesis clearly show that model predictions in drainage systems are uncertain - especially if models are un-calibrated. The most important uncertainties are:

- The *rainfall input*. Use of historical rain series from point measurements are not necessarily representative for whole catchments. Furthermore, rain series are often too short to estimate the return periods of failure with significant probability.
- The so-called *hydrological reduction factor*. This parameter determines the part of the impervious area which contributes to the runoff. Even though this parameter is estimated by calibration, the dispersion of the values is quite large. As a result the variations in modelled volumes are large.

Based on the complete study it is recommended, when using urban drainage models, to try to improve input and calibration data, so that the model predictions can be estimated more accurately. For non-research use of models, it is not applicable to implement Monte Carlo simulations as these require thousands of simulation hours. However, it is recommendable to conduct some minor sensitivity analyses, e.g. by modelling the catchment in question with different rain series and carefully selected values of the hydrological reduction factor.

## Danish summary (Dansk resumé)

Anvendelsen af numeriske hydrodynamiske modeller til analyse af afløbssystemer er i de senere årtier blevet mere og mere udbredt blandt rådgivende ingeniører, kommuner, mv. Modellerne giver et detaljeret overblik over afløbssystemets funktion under regn, fx med hensyn til opstuvning til kritiske niveauer og recipientoverløb. Dog er brugen af modellerne i høj grad forbundet med tradition, erfaring og empiri hvad angår valg af modeller, modelparametre og modelinputs. For at sikre overholdelse af dimensioneringskriterier implementeres, delvis på grund af manglende viden, en ofte stor sikkerhed i valget af modelparametre, hvilket i nogle tilfælde kan resultere i overdimensionerede afløbssystemer - eventuelt med en dårlig selvrensningsevne til følge. På den anden side, hvis den fornødne sikkerhed ikke implementeres opstår der risiko for underdimensionering af det pågældende afløbssystem og deraffølgende unødige oversvømmelser og recipientoverløb. På baggrund af ovenstående er der et, både samfunds- og ingeniørmæssigt, stort behov for at undersøge usikkerhederne ved anvendelse af numeriske afløbsmodeller både hvad angår usikkerhed på input og parametre samt prædiktionsusikkerhed.

Ved at klarlægge disse usikkerheder og tage højde for dem stokastisk kan der opnås væsentlig bedre og mere pålidelige modelresultater, hvilket i sidste ende kan reducere både anlægsudgifter og skadesomkostninger.

Nærværende afhandling består af en indledende registrering og kvantificering af usikkerhedsbidrag. Hernæst er der på baggrund af de væsentligste valgte usikkerheder udført modelsimuleringer med tre forskellige stokastiske metoder med det formål at forplante usikkerhederne på inputs og parametre gennem modellen til et usikkerhedsestimat af modelprædiktionerne. De gennemførte beregninger er eksemplificeret ved hjælp af mindre afløbssystem i byen Frejlev, beliggende få kilometer uden for Aalborg, Danmark.

Den første af de anvendte stokastiske metoder, er en sandsynlighedsteoretisk metode som søger efter svigt i modelrummet. Svigt er i denne sammenhæng defineret som enten opstuvning til rørtop (*eng. surcharge*), opstuvning til terræn (*eng. flooding*) og forekomst af recipientoverløb. Metoden indebærer en parameterisering af regninputtet til modellen, således at det er muligt at generere kunstige Gauss-formede regnhændelser. Denne iterative søgealgoritme har vist sig at være meget anvendelig til at finde svigt i afløbssystemer og anses derfor som et muligt alternativ til traditionelle analyser, især fordi den både tager højde for usikkerhederne på regninputtet og de forskellige parametre.

Den anden af de stokastiske metoder, er en Monte Carlo baseret stokastisk kalibrering, der anvender den såkaldte GLUE-metode (Generalized Likelihood Uncertainty Estimation). Denne indebærer en hændelsesbaseret konditionering af afløbsmodellen ved brug af vandførings- og overløbsobservationer i afløbssystemet. Hermed er det både muligt at finde de parameterfordelinger som giver den største korrelation mellem observerede og modellerede tidsserier, samt at undersøge forskellige konceptuelle opsætninger af afløbsmodellen med

det formål at finde den mest pålidelige modelstruktur. Metoden viser sig særdeles anvendelig til modellering af afløbssystemer, dog har det ikke været muligt at få modelprædiktionsernes konfidensintervaller til at dække de observerede tidsserier fuldstændigt.

Den sidste stokastiske metode anvender resultaterne fra de to foregående analyser ved at modellere ekstremstatistikkerne i afløbssystemet ved hjælp af Monte Carlo simuleringer. For at tage højde for usikkerhederne forbundet med gentagelsesperioderne er der foreslået en ny metode, hvori gentagelsesperioderne for hhv. maksimale vandstande i brønde og overløbsvolumener beregnes ud fra nogle opstillede korrelationer mellem input og respons i afløbssystemet. Desuden anvendes en statistisk model for gentagelsesperioderne for nogle karakteristiske regnparametre. Hermed har det været muligt at belyse usikkerhederne forbundet med frekvenserne for opstuvning til kritiske niveauer og recipientoverløb. Disse viser sig at være forholdsvis store især på de lange gentagelsesperioder.

Analyserne foretaget i denne afhandling viser med al tydelighed, at modelprædiktions i afløbssystemer er usikre, især hvis modellerne ikke er kalibrerede efter lokale målinger. De vigtigste usikkerheder har vist sig at være:

- *Regninputtet til modellerne.* Brug af historiske regnserier fra punktmålinger er ikke nødvendigvis repræsentative for hele det modellerede opland og regnserierne er ofte for korte til, med en signifikant sandsynlighed, at estimere gentagelsesperioderne for svigt i afløbssystemet.
- Den såkaldte *hydrologiske reduktionsfaktor*. Denne parameter kontrollerer hvor stor en del af det befæstede areal, der bidrager til afstrømningen. Selvom denne er kalibreret på plads, er der en forholdsvis stor spredning på værdierne, hvilket gør at volumenerne i modellen varierer meget.

På baggrund af det gennemførte projekt anbefales det, ved anvendelse af afløbsmodeller, at forsøge at forbedre input- og kalibreringsdata, med henblik på mere pålidelige prædiktions. Det er ikke direkte anvendeligt, for ikke-forskningsbaseret anvendelse af modeller, at gennemføre Monte Carlo simuleringer, idet dette kræver adskillige tusinde simuleringstimer. Herimod kan det anbefales at lave nogle mindre sensitivitetsanalyser, for eksempel ved at gennemregne det pågældende opland med flere forskellige regnserier og udvalgte værdier af den hydrologiske reduktionsfaktor.

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<b>Paper VII .....</b>	<b>193</b>
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# Chapter 1

## Introduction to urban drainage

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*In this chapter a short review of the history of urban drainage is presented. The historical review leads to a description of the current design practice for urban storm water systems in Denmark. Uncertainties and problems related to current design practice are presented along with challenges for design and function of storm water systems in the future.*

### 1.1 History of Urban Drainage

The history of urban storm water drainage dates back to civilizations such as Mesopotamia, the Greek Antiquity, and Ancient Rome. Here, storm water from buildings, important squares etc. was collected in open or closed channels and discharged to the nearest receiving water. The most famous is the still existing Cloaca Maxima draining Forum Romanum in the ancient Rome. (Butler and Davies 2004, Winther et al. 2006)

Until the 18th century waste water in cities was discharged to local cesspits which were manually emptied. During this century, however, construction of the first waste water and storm water collection systems began along with the development of the flushing WC. Both the cesspits and the open channelled collection systems were effective disease carriers and contributed to large cholera epidemics in the 1900th century. This was one of the reasons why collection in closed channels and pipes was initiated during this century. After the first quarter of the 20th century, most western cities had combined collection systems for both waste and storm water in the form of pipe systems. However, sanitary problems were just repositioned from the city to receiving waters. Nevertheless, it was not until the 1970's that a specific treatment of waste water began in European cities (Butler and Davies 2004, Winther et al. 2006).

In Denmark, a separation between waste water and storm water was initiated for new systems during the 1970's and this work is still ongoing. The concept is that organic material, nitrogen, and phosphorus (macro pollutants), must be removed from waste water at a waste water treatment plant (WWTP) before emission to receiving waters. Storm water, however, contains significantly smaller amounts of macro pollutants, and is discharged directly to receiving waters without any treatment, although often delayed in detention ponds in order to prevent erosion or flooding in receiving waters. In recent years, storm water, especially

from roads, has been investigated quite intensively as it contains various micro pollutants such as heavy metals and organic compounds that are non-detergent in nature. The tendency, however, is that more and more separate systems are constructed in urban areas. As an example, it is worth mentioning that the Municipality of Aalborg defined a vision of completely separated systems before the year 2100 (Aalborg Kommune 2006).

As described, the development of separate drainage systems is still an ongoing process. The sewer system used as case in this study is a hybrid system, i.e. a partly separated and partly combined system (presented in Chapter 3). Thus, the case represents the ongoing developments.

## 1.2 Design practice in Denmark

In the 1930's six Danish municipalities installed rain gauges to measure precipitation on a small temporal scale, as the temporal resolution of the existing rain gauge data was too large to be used for design purposes of storm water systems. Based on these data, design practices and guidelines were published by The Water Pollution Committee of The Society of Danish Engineers (Spildevandskomiteen 1950, 1953, 1974). Spildevandskomiteen (1974) is still used by many consultants for design purposes. With some intermissions, these six rain gauges recorded until 1979, when a national grid of new rain gauges was installed by the Water Pollution Committee of The Society of Danish Engineers (and paid by the municipalities). At first, this led to installation of 43 rain gauges. Statistical analysis (using intensity-duration-frequency relationships, IDF) of recordings from these gauges are presented in Spildevandskomiteen (1999) covering the period from 1979 to 1996. More gauges were installed and an extended set of data was presented in Spildevandskomiteen (2006) covering the period from 1979 to 2005. Currently, a total of 104 rain gauges (in 2008) constitute the Danish national grid.

Using the IDF-relationships derived from the rain gauge data, it is possible to generate design storms (with a constant intensity in a given period of time) as input to e.g. the Rational Method or the Time-Area method in order to design storm water systems (Butler and Davies 2004, Winther et al. 2006). Both methods are based on a linear relationship between the rainfall intensity and corresponding flow in the pipes. Applying these methods, it is only possible to predict full-running flow and hence not possible to predict the water level if the pipe top is exceeded i.e. occurrence of surcharge or flooding (if ground level is exceeded). Nor are backwater effects normally considered.

According to the Danish practice of drainage systems during rainfall (Spildevandskomiteen 2005), the simple design methods correspond to the lowest level of calculation, in which the following criteria must be met in urban areas:

- The return period of surcharge must exceed 2 years for combined sewer systems.
- The return period of surcharge must exceed 1 year for separate storm water systems.

*Table 1.1 Recommended design frequencies. From European Standard for Drain and Sewer Systems Outside Buildings, European Standard no.: EN 752-4 (1997)*

Design storm frequency* 1 in n years	Location	Design flooding frequency 1 in n years
1 in 1	Rural areas	1 in 10
1 in 2	Residential areas	1 in 20
	City centres/industrial/commercial areas	
1 in 2	- with flooding check	1 in 30
1 in 5	- without flooding check	-
1 in 10	Underground railway/underpasses	1 in 50
* For these design storms, no surcharge shall occur		

The European Standard for Drain and Sewer Systems Outside Buildings, European Standard no.: EN 752-4 (1997) specifies the criteria presented in Table 1.1. Existing frequency requirements from any relevant local authority, however, overrule the recommendations of EN 752-4.

One disadvantage of the simple design methods is that they can not be used for prediction of combined sewer overflow volumes due to the use of design storms. In order to predict these volumes, real rainfall time series has to be used requiring more complex prediction methods.

The Rational method and the Time-Area method do not handle backwater effects and water levels above the pipe top and are therefore not recommendable when dealing with large systems with many manholes and overflow structures, detention basins, etc. In applications with more complex systems it is recommendable initially to use one of the simple design methods and secondly to analyse the whole system using a simulation based model, as presented in the next section.

The calculation level above the Rational Method and the Time-Area method, the Chicago Design Storm (CDS), is also based on design storms, but implemented in simulation based modelling tools, so that backwater effects, flooding, headlosses, etc. can be included.

Compared to the IDF design storms in which only one rainfall intensity at a given aggregation level (duration) is applied at a time, the concept of the Chicago Design Storm (Kiefer and Chu 1957) is that a whole series of IDF design storms can be combined to one single conceptual event, covering all possible rainfall intensities with a specific return period. Thus, it is possible, in one single simulation, to analyse a drainage system e.g. for occurrences of surcharge or flooding. It is still assumed, however, that the return period of the rainfall intensity equals the return period of the water level in the manholes and pipes.

The third and highest level of computation according to Spildevandskomiteen (2005) differs from the other approaches as real measured rainfall time series are used as input for the model. Using historical rain series it is possible to predict surcharge, flooding, combined sewer overflow, etc. and combine these with a return period, which is based on the actual simulation occurrence in the system and not the return period of a given rainfall intensity.

Several commercial models exist and these can handle the level of computations presented in this section. They are to some extent based on the same theoretical foundation, for example the SWMM model (Storm Water Management Model) developed by the U.S. Environmental Protection Agency or the InfoWorks CS model (formerly HydroWorks), which is developed by Wallingford Software, United Kingdom. However, the model which is used by the vast majority of consultants in Denmark is the MOUSE model (MOdelling of Urban SEwers), developed by the Danish company DHI (Lindberg and Willemoës Joergensen 1986). The MOUSE model contains a statistical tool for long term statistics (MOUSE-LTS, Jakobsen et al. 2001), which computes return periods of e.g. maximum water levels, overflow volumes, etc. Before this tool was developed, the simple modelling tool, SAMBA, was used rather extensively by consultant engineers for prediction of overflow volumes (Johansen 1985). This is based on the Time-Area method (for both surface and pipe flow) and historical rain series. This model has the advantage that a simulation can be completed in a very short period of time compared to a long term MOUSE model.

According to the Danish practice of drainage systems during rainfall (Spildevandskomiteen (2005), the second and third level of computation must be based on the following criteria:

- The return period of flooding must exceed 10 years for combined sewer systems
- The return period of flooding must exceed 5 year for separate storm water systems

The design process for larger drainage system is thus divided in two parts.

1. A simple design process using the Rational- or the Time-Area method in combination with IDF-relationships (This was formerly the only part of the design process)
2. An analysis of the designed system, using a model based simulation tool, in order to investigate if the specified return periods of flooding are exceeded. This approach can be based on either a CDS rain input or long term simulations with historical rain series.

Often the simulations are carried out on existing systems in which the design was only based on (1). Therefore, it might not be fair to conclude that a system does not meet the specified return periods of flooding if the system was designed before the two part design methodology was implemented in Spildevandskomiteen (2005). This is the case with the catchment used in this thesis.

### 1.3 Uncertainties

For many years, the traditional code of practice was to design the drainage system in question by one of the simple calculation methods. Calculation parameters, such as impervious surface areas, surface concentration time, etc. were selected with a large safety margin, and furthermore pipe diameters were selected by rounding up the computed pipe diameter to commercial pipe dimensions with one or two steps. Possible model computations to examine the whole system would then show, due to the implemented safety, that no surcharge or

flooding occurred within the return period criteria. In many cases, this approach has worked well as most calculations were implemented with large safeties, and the number of flooding occurrences due to poor functioning systems was kept at a reasonable level.

Due to this practice, in some cases, the drainage systems might be over-dimensioned causing excessive construction expenses and potentially problems e.g. with poor self cleaning in dry weather conditions. On the other hand, if the system is under-dimensioned, unnecessary flooding and combined sewer overflow might occur, with potential health problems and other inconveniences as well as pollution of receiving waters, as a consequence.

Partly due to the growing debate on climate changes and partly to some extreme isolated heavy rainfall events in Denmark the recent years, the focus on analysis has shifted within this area. It is for example recommended in Spildevandskomiteen (2005), that the modeller select values of calculation parameters as close to the reality as possible, without implementing any safety in the selections. It is, however, recommended to take care of the uncertainty a posteriori to the calculation by multiplying the design flow by a certain safety factor. It is, however, difficult simply to choose realistic and adequate parameters that represent the drainage system in any conditions. Moreover, a great part of urban drainage model uncertainty is a result of insufficient or uncertain inputs (e.g. if the rainfall input time series does not represent the whole catchment).

The model output uncertainty can be reduced by checking the model against some observed data from existing systems. If adequate data is present, a calibration can be conducted but for non-research purposes this is very rarely seen.

The prediction uncertainty easily adds up to several hundred percent on maximum water levels and overflow volumes (especially on the long return periods) if a model is not calibrated, resulting in a significant need for more research in order to find the main uncertainties in the models and to give suggestions for handling and reduction of these uncertainties.

## 1.4 Urban drainage in the 21st century

One of the great challenges for urban drainage engineers in the forthcoming years is to handle the likely increases in precipitation volume and frequency due to climate changes. Some authors have already investigated the subject, e.g. Arnbjerg-Nielsen (2006), Grum et al. (2006), Mark and Linde (2006), Olofsson (2007), Ashley et al. (2005). Climate changes have lead to new thoughts on how to handle storm and waste water in urban areas. For example by local infiltration of storm water, or reuse of clean storm water within the cities by construction of channels and ponds. Furthermore, the use of real time control (RTC) in drainage systems may help meet some of the challenges caused by the climate changes as well as help reduce overflow of untreated water to receiving waters.

Some new developments concerning forecasting of flows and water levels in drainage systems using weather radar data are currently researched. These forecasts can be beneficial for real time controls and in combination with warning systems this may help inform the

population if massive flooding is expected. New developments in modelling tools, e.g. to simulate flooding on urban surfaces in two dimensions, may also help create risk assessment of urban areas if the climate scenarios given by the International Panel on Climate Change (IPCC 2001, 2007) becomes reality.

Presented in this section are all arrangements that are currently researched intensively, but despite of their relevance not considered any further in the thesis.

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## Chapter 2

# Thesis statement and structure

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*This chapter presents the definition of problems concerning uncertainties in urban drainage modelling as well as an outline and limitations of the thesis.*

### 2.1 Concept of the thesis

Consulting engineers, municipalities, etc. frequently use drainage models to analyze urban drainage systems' ability to function during rain, in order to predict flooding of critical levels and overflows from combined sewer systems to receiving waters, and the return periods related to these. The use of models is highly dependent on tradition and empirical assumptions concerning the choice of models, model parameters, and also whether or not model calibration is possible. When using the models to analyse new drainage systems to make sure the design criteria are met, and partly due to a lack of knowledge concerning choice of parameter values, a great safety margin is often implemented in the model simulations. In some cases, this can lead to over-dimensioned sewers, causing excessive construction costs, and potentially, problems with poor self cleaning. On the other hand, however, if the necessary safeties are not implemented in the models, the sewer design involves frequent flooding of certain areas or frequent overflows from combined sewer systems to receiving waters. Thus, from a social and an engineering point of view there is a need for research in uncertainties, in both input and output of urban storm water drainage models. Such knowledge will help users of such models to produce more valid and reliable results, especially when analysing existing systems.

During the past decades, when the use of urban drainage models has evolved, a fascination with the possibilities within these models, has neglected the fact that results are uncertain to some extent. This is evident when looking at the number of publications within this area of research; few authors have investigated uncertainties related to modelling of urban drainage systems before 2000. Aronica et al. (2005), Lei (1996), Willems and Berlamont (1999), Clemens (2001), Vojinovic (2007), Arnbjerg-Nielsen and Harremoes (1996b), and Hansen et al. (2005) have investigated uncertainties in urban drainage modelling in general. Grum and Aalderink (1999), Grum (2001), Zhu and Schilling (1996), Korving and Clemens (2002), Arnbjerg-Nielsen and Harremoes (1996b), and Harremoes (1994) have investigated uncertainties in combined sewer overflow prediction. Choi and Ball (2002), Clemens



(2001), di Pierro (2006), Khu et al. (2006), Wangwongwiroj et al. (2004) have investigated calibration of urban drainage models. Several authors have investigated uncertainties related to rainfall input. These are presented in Chapter 7.

The main purpose of this thesis is to make a general uncertainty estimation of urban drainage models, focusing primarily on long term statistics of the drainage system in question. That is both long term statistics of surcharge and flooding in the individual manhole as well as long term statistics of outlets and overflows to receiving waters.

The idea is to use the conventional deterministic modelling approach as a starting point, and attempt to account for the input and parameter uncertainties by using stochastic modelling approaches. Instead of using one value for each input and parameter, resulting in a single output, probability density functions for inputs and parameters are applied in a large number of model simulations. The model predictions can then be propagated as a discrete probability density function. It is therefore possible to determine the probability of exceeding a given value, e.g. maximum water level in a manhole exceeding ground level.

There are numerous subjects to be investigated concerning stochastic modelling and uncertainty estimation in urban drainage systems, both with regards to uncertainty reduction of inputs and parameters as well as methods of implementing the uncertainty estimation in the existing framework of urban drainage models. It is a question of which stochastic methods are preferable to use in the context of urban drainage modelling and also how model data (inputs and parameters) must be specified and processed in order to make a valid uncertainty estimation.

The study is limited with regards to handling the uncertainties stochastically and not necessarily reduction of them, except in one stochastic calibration approach, presented in Paper VI. Furthermore, the study is delimited to investigate the *analysis* of urban drainage systems - not the *design* or *reconstruction*. For that reason, only the more advanced simulation tools are considered, opposed to the simple design methods. Moreover, if capacity and overflow problems are observed in the drainage system using the model results, suggestions or possibilities of reconstruction are not considered.

Finally, climate changes are not considered in this study, despite the relevance of implementing the uncertainty associated with this phenomenon. It is, however, the author's opinion that in order to model the future, one must initially be able to model the past in an adequate way. Therefore the study is based on the assumption that observed rainfall input observed in the past is representative for the future.

The thesis is based on a case study using one catchment, the Frejlev catchment, which is chosen due to exceptional flow and rain measurements. However, the results from the study should be applicable for other catchments as well; at least on catchments with the same characteristics (residential areas with mainly detached houses). The catchment is presented in Chapter 3.

## 2.2 Thesis structure

The thesis is divided into two parts:

1. An initial registration of all contributions of uncertainties and statistical parameterisation of input data, model parameters, observation data, choice of model complexity, etc. Primarily obtained by literature review, statistical analysis of observations, and deterministic model testing. This part of the thesis is presented in Chapter 3 to 9, as well as Paper I - III and the appendices.
2. Implementation of stochastic methods on urban drainage models in order to transform error and uncertainty contributions of input and model parameters to an estimation of uncertainties of model outputs. This part of the study is presented in Chapter 10, as well as Paper IV to VII.



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## Chapter 3

### The Frejlev catchment

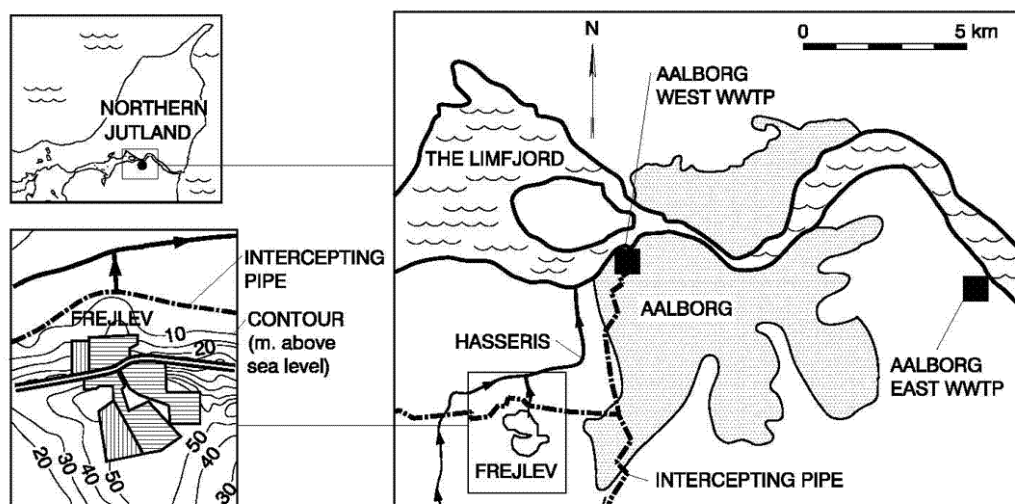
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*The following chapter presents the Frejlev catchment, which is used as case through out this thesis.*

#### 3.1 General description

Frejlev is a small town close to Aalborg in Northern Jutland, Denmark, with approx. 2100 inhabitants and an area covering approx. 90 hectares. During dry weather waste water from the town is discharged to Aalborg Waste Water Treatment Plant West through approx. 8 km of pipeline. During rain, a combined sewer overflow discharges a mixture of waste water and storm water to a small stream, Hasseris Å, and further to the Limfjord. (Figure 3.1) This happens approximately 20 times per year. The yearly mean flow rate in Hasseris Å, is approx  $0.3 \text{ m}^3/\text{s}$  (Nordjyllands Amt 2006).

The Frejlev catchment is located on a hill, the Southern part of the town is approx. 50 m above sea level and the Northern part approx. 10 m above sea level, Figure 3.1.



*Figure 3.1 Aalborg, the town of Frejlev, the small stream Hasseris Å, and the Aalborg West waste water treatment plant (WWTP). Schaarup-Jensen et al. (1998).*

### 3.2 The sewer system

The sewer system in Frejlev is a hybrid system, consisting of both separate sewer systems for storm and waste water as well as a combined system in the oldest part of the town. According to Aalborg Kommune (2006), the goal is to separate the sewer system before the year 2100 and preferably sooner. The sewer system consists of a little more than 550 main manholes, two weirs, three retention basins, and one pump (Figure 3.2 and 3.3). A 70 m long (1600 mm diameter) in-line detention storage is located just upstream from the combined sewer overflow. Since 2004 some other basins and weirs have been added to the system, as separate systems have been constructed in the North-Eastern part of the drainage system. However, the drainage system considered in this study is the system as it was before changes were made.

The catchment mainly consists of detached houses, some terrace houses, a school and a small centre with a few shops and light industry. The total catchment area is approx. 87 ha and the catchment consists of 620 houses (corresponding to approx. 17 ha), approx. 9 ha of road areas and 2 ha of pavement areas. Including some other minor contribution the total impervious area adds up to 35 ha (40 %) when all possible contributions are accounted. In Paper I different definitions of the impervious area are investigated.

The digitalization of the sewer systems is based on work by the consulting engineers NIRAS (in 2001) and originally the digitalisation of the catchment was also based on this work; however a new digitalisation of the catchment area was performed in Paper I.

### 3.3 The monitoring and research station

The Frejlev catchment has been continuously monitored with two electromagnetic flow meters since 1997. In order to be able to measure the runoff flow from the catchment very accurately in both wet and dry weather, *two* flow meters were installed. The first on a 300 mm pipe with a maximum flow of 80-100 l/s and the second meter on a 1000 mm pipe measuring flows from 50-3500 l/s. The discharge from the town is divided in an internal overflow structure. In case of a full-running pipe, the flow is discharged to the 1000 mm pipe (Figure 3.3).

The flow meters are of the Parti-Mag II type manufactured 1996 by Bailey-Fischer and Porter in Göttingen, Germany. According to the manufacturer the error on both meters are in the range of 1-1.5% of rating. Schaarup-Jensen et al. (1998)

Until now, measurements from this station have been subject to various investigations, e.g. sediment transport (Schlutter and Schaarup-Jensen 1998), dry weather flow (Schaarup-Jensen and Rasmussen 2004), exfiltration (Vollertsen and Hvitved-Jacobsen 2003), and the papers included in this thesis. Furthermore, several students on bachelor and master level have studied the catchment.

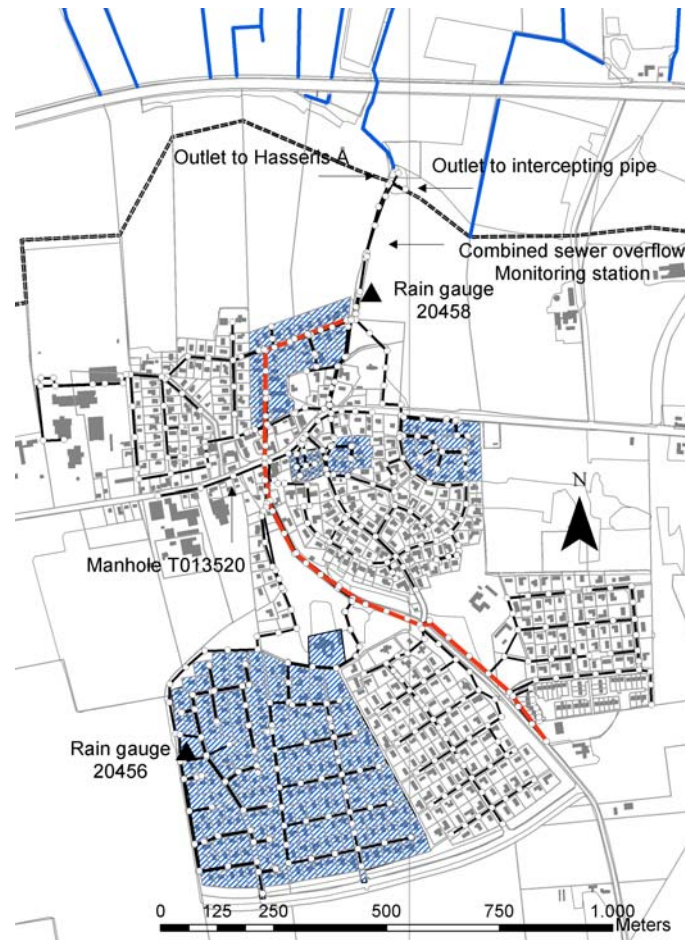


Figure 3.2 The Frejlev sewer system. Blue areas are catchments with a separate sewer system, the rest is a combined system. The thick red line is the main sewer line.

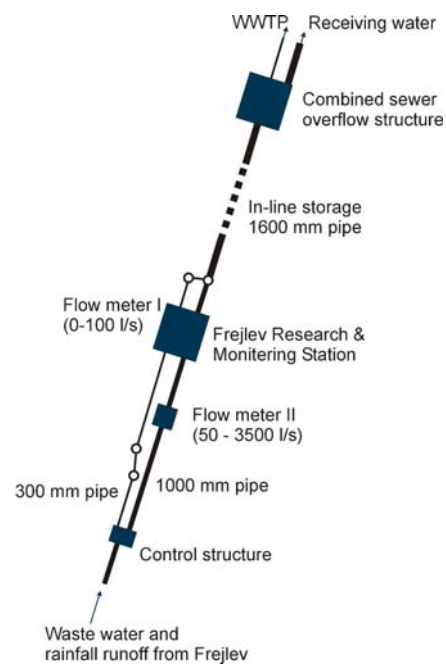


Figure 3.3 Schematic overview of the flow meters

Besides the flow measurements, the Municipality of Aalborg monitors the occurrence of overflow, using an on-off switch in the CSO-structure. This switch logs binary data every 4 minutes indicating if there is overflow or not.

### 3.4 The rain gauges

The flow measurements are supplemented by two automatic rain gauge stations which are included in the Danish national rain gauge system managed by the Danish Waste Water Control Committee and operated by the Danish Meteorological Institute. One of the rain gauges (gauge no. 20458, Figure 3.4 and 3.6) is placed on top of the research station, 15 m above sea level. The second one (gauge no. 20456, Figure 3.4 and 3.5) is placed uphill, 55 m above sea level, in the South-Western part of the town at a distance of approx. 1.2 km from gauge no. 20458. The two gauges in Frejlev have been recording since 1997. In addition, a third rain gauge (the Svenstrup gauge, no. 20461, Figure 3.4) is placed approx. 4 km south of Frejlev, and has been recording since 1979. The three gauges are all of the Rimco tipping bucket type.

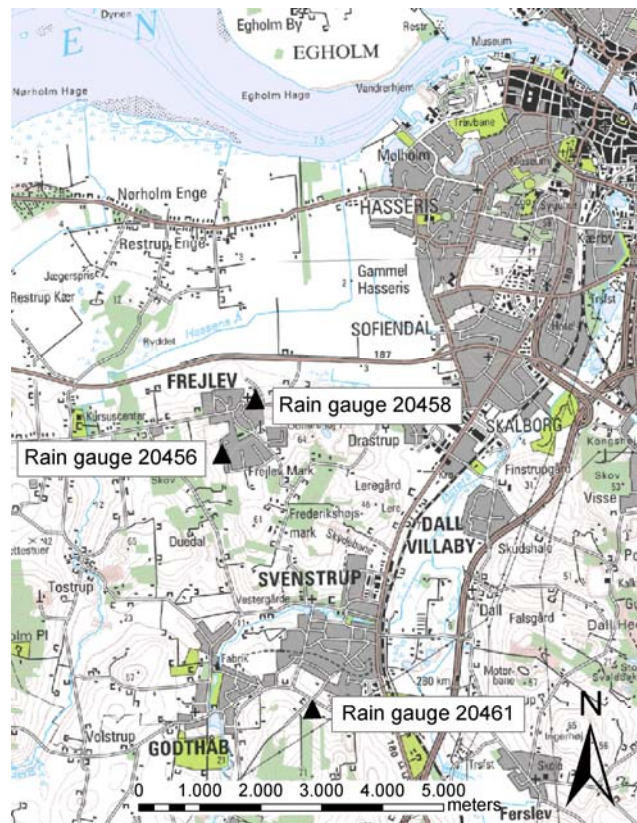


Figure 3.4 Map of the Frejlev area with three rain gauges.



*Figure 3.5 Photograph of the Frejlev South rain gauge, no. 20456*



*Figure 3.6 Photograph of the Frejlev North rain gauge, no. 20458*





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## Chapter 4

# Uncertainties in urban drainage modelling

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*The following chapter presents a definition of uncertainties, which can be used generally within the field of modelling (Chapter 4). In Chapters 5 - 9, more specific descriptions of processes and theory within urban drainage and related uncertainties are presented.*

### 4.1 Preliminary uncertainty definitions and characterizations

The object of uncertainty analysis and uncertainty modelling in general is to transform uncertainties of the input to an uncertainty estimate of the output. This and the forthcoming chapters aim, primarily by literature review, to map, group, and limit the main uncertainties related to the input and setup of urban drainage models. Chapter 10 and Papers IV - VII present methods to handle the uncertainty.

Before assessing uncertainties in urban storm water drainage modelling, it is important to initially have a distinct definition of the different types of uncertainties, and secondly to know the origin of the uncertainties, and finally, know how to quantify them. Models are always an approximation to reality and all parts of a model are by definition uncertain. If one is not aware of the main locations of uncertainties, the model output uncertainty quantification becomes useless.

### 4.2 Uncertainty and model definitions

When defining the overall uncertainties in urban drainage modelling, and in modelling in general, it is important to have distinct definitions of the different sources of uncertainty in order to handle the uncertainties in a proper manner. Several authors have defined modelling uncertainties in general e.g. Beck (1987), Walker et al. (2003), and Beven (2008), but only few have defined uncertainties in the context of urban drainage Lei (1996), Willems (2000b), and Hauger (2005). In the present thesis another distinct definition of uncertainties regarding urban drainage modelling is presented as this has shown to be useful in the applications applied in this thesis.

The overall uncertainties can be divided into two types: simulation input uncertainties and prediction uncertainties (or simulation output uncertainties). The prediction uncertainty is the consequence of simulation input uncertainties and hence the objective of the entire study. The following are therefore based on the simulation input uncertainties.

A logical way of dividing the simulation input uncertainties is to investigate if the uncertainties can be reduced or handled, e.g. by calibration, by an increase in the level of detail, or by randomization. By these definitions it is possible to divide simulation input uncertainties into five different groups, namely:

1. *Model methodological uncertainties*, which concern choice of models and if processes are adequately presented by the theory and physical laws.
2. *Physical structure uncertainties* cover parameters specific for the catchment and sewer system in question. These parameters are not calibrated or randomized contrary to the calculation parameters.
3. *Input data uncertainties* covers model input boundary conditions which vary in time.
4. *Calculation parameter uncertainties* cover parameters which are not specific to the catchment and sewer system in question. Contrary to the physical structure these parameters are calibrated and/or randomized.
5. *Observation data uncertainties* cover uncertainties related to calibration data.

This pentad of uncertainties is illustrated in Figure 4.1. Obviously, the definitions are not unambiguous (illustrated by the overlaps of the ellipses). It is for example preferable, in one model setup, to handle a certain parameter by randomization and in another by an increase of model complexity or maybe both. The elements of the pentad are presented individually in Chapters 5-9 and in Table 4.1 the characteristics of the pentad elements are explained along with the terminology of other authors.

*Table 4.1 Reducing and handling uncertainties*

	Uncertainty can be re- duced by calibration	Uncertainty can be reduced by in- crease of model complexity	Can be hand- led stochasti- cally	Denotation in Lei (1996)	Denotation in Willems (2000b)
Input data	-	+	+	Model inputs	Inputs
Calculation parameter	+	+	+	Model parameters	Parameters
Physical structure	-	+	(+)*	System attributes	Parameters
Model methodology	-	+	-	Model structure	Model structure
Observation data	-	-	-	-	-

\* The physical structure can be, but is most often not, handled stochastically

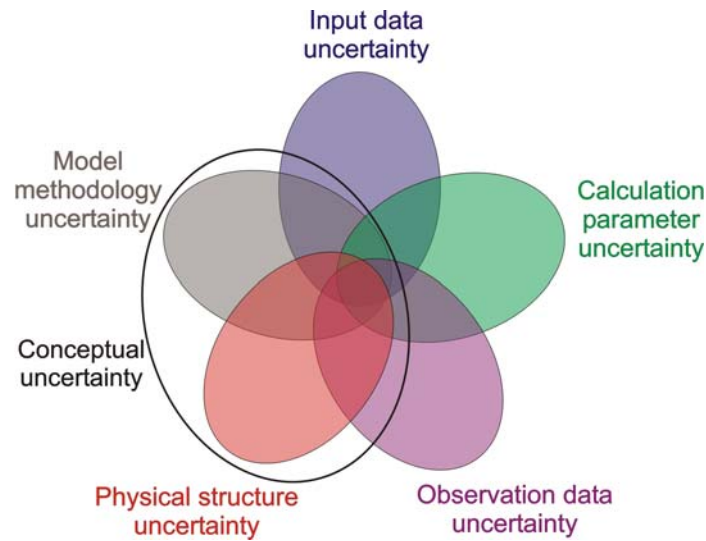
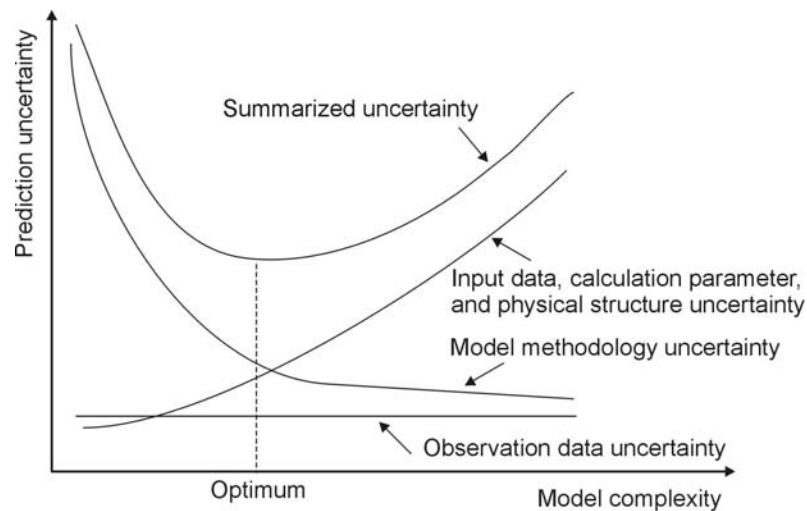


Figure 4.1 Pentad of simulation input uncertainties. The model methodology uncertainty and the physical structure uncertainty can be defined as conceptual uncertainty.

Walker et al. (2003) divides the nature of uncertainty in two, specifically epistemic uncertainty (due to imperfection or lack of knowledge) and variability uncertainty (due to natural variability). In order to classify the origin (or nature) of uncertainties in a more practical applicable way, the uncertainties are presented in this thesis as either: *systematic uncertainty*, *random uncertainty*, or *uncertainty by estimation*. This definition is independent of whether or not the uncertainty is due to a lack of knowledge or a natural variability. In addition Lei (1996) defines a fourth uncertainty nature namely a *spurious error*, defined as a value exceeding reasonable limits. Errors of this type can also be characterized as outliers.

The origin of the uncertainties is important in parameterization and assessment of the overall prediction uncertainties, as the modeller must know if it is advantageous to handle the parameter in question by randomization, calibration, or by an increase of model complexity.

In Figure 4.2 the interdependence between the different parts of the pentad is presented. The figure illustrates that there is an optimum between the number of inputs (input data, calculation parameters, physical structure and observation data) and the model methodology complexity. The probability of parameter and input uncertainties or errors grow as a function of model complexity, i.e. as more parameters and inputs are applied. On the contrary, as the model complexity increases the model methodological uncertainty evidently decreases. Additionally, the observation data uncertainty is shown as a constant value since this is not influenced by model complexity. The minimum of the summarized uncertainty curve therefore represents the optimum between the uncertainty of parameters and inputs and the model methodology uncertainty.



*Figure 4.2 Simplified diagram showing the contributions to the total (summarized) model output uncertainty as a function of model complexity (or the number of parameters), freely adapted from Jensen (2002), Willems (2000b).*

The model methodology uncertainty can not be handled stochastically and it is preferable, when applying stochastic modeling, to increase the model complexity and with that also the number of parameters, as parameters can be randomized. Therefore, it is possible that implementation of stochastic models does not aim at the optimum, as it is the case in deterministic models.

Beven (2006) has introduced the equifinality thesis dealing with the prediction uncertainty. The idea is that it is possible to obtain the same model output using different parameter sets. For example, in a simple model with two parameters the same result might be obtained by using a high value of one parameter and low value of another parameter and visa versa. Then it is possible for many different model setups to predict acceptable results, especially if a model is over-parameterized. If validation data is available it is preferable to test this using another input.

In the following chapters the elements of the pentad (Figure 4.1) are presented individually in the context of urban drainage modelling.

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## Chapter 5

# Model and methodological uncertainty

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*This chapter presents an outline of the theoretical and methodological background for urban drainage models and explains the origin of model methodological uncertainty, i.e. how well the different processes represent reality and if the processes are adequate.*

### 5.1 Urban drainage models

The setup of an urban drainage model can be very large and complex, because of the need to predict flows, water levels, overflow volumes, etc. for whole catchments and due to the fact that the catchments often contain several hundred or more manholes and pipes. Even though the mathematics of the model and sub-models are somewhat easily programmed, it is decided to use commercial urban drainage software packages in the present study. The commercial models are produced to handle the great amounts of data and are important tools for consulting engineers. Therefore, the results of this thesis may be directly applicable for others users of commercial models. Furthermore, commercial models have shown to be both reliable and with an acceptable complexity, as to what is needed in this study. Several models exist and they are to some extent based on the same theoretical foundation, for example the SWMM model (Storm Water Management Model) developed by the U.S. Environmental Protection Agency or the InfoWorks CS model (formerly HydroWorks), which is developed by Wallingford Software, United Kingdom. However, the model which is used by the vast majority of consultants in Denmark is the MOUSE model (MOdelling of Urban SEwers), developed by the Danish company DHI (Lindberg and Joergensen 1986). This study is completed using this model, but one of the other models could also have been applied. Recently, a GIS-based interface, named MIKE Urban, is implemented on the basis of the MOUSE model, but in this study the MOUSE version 2004 is applied.

## 5.2 The MOUSE model

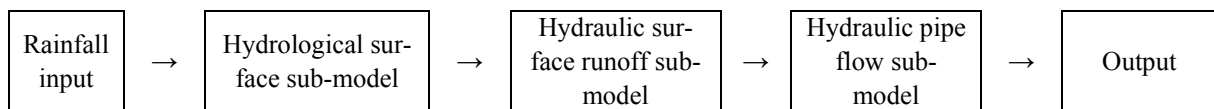
The MOUSE model consists of three different sub-models as presented in Figure 5.1. These are: the hydrological surface sub-model which determines the part of the input which contributes to the runoff; the hydraulic surface runoff model which routes the water from the surface to manholes; and the hydraulic pipe flow model which transports the water in the sewer system. Furthermore, some add-on processes can be linked to the MOUSE model, e.g. a water quality sub-model, a sediment transport sub-model, etc. These are, however, not applied in the present study.

The next section will focus on each of the three sub-models, describing the general theoretical and methodological background, as well as the most important model uncertainty.

## 5.3 Hydrological surface sub-model

A hydrological surface sub-model determines the runoff volumes from a catchment, i.e. the hydrological reduction of the precipitation. This part of an urban drainage model is traditionally associated with considerable uncertainty, as it is difficult to determine which sub-surfaces actually contribute to runoff. Furthermore, it is uncertain how precipitation is reduced on these surfaces, due to wetting, soil infiltration and evaporation.

The simplest method of modelling runoff volumes is to apply a linear relationship between the runoff and the precipitation volumes (depths), i.e. the runoff volume is calculated as a percentage of the precipitation subtracted the initial loss (Winther et al. 2006, DHI 2003b), Paper I and II). The linear relationship can be either in the form of a hydrological reduction factor, which is percentage of impervious surface area that contributes to the runoff, or as a runoff coefficient, which determines the percentage of the total surface area that contributes to the runoff. Such linear reduction models are easy to calibrate when flow measurements are available, but can be uncertain, due to the assumption of independence between the contribution area and precipitation intensity. A comprehensive description of the hydrological surface model is presented in Chapter 8.



*Figure 5.1 Structure of the MOUSE model*

Contrary to the hydrological reduction factor model, in which the reduction of the rainfall input is constant in time, a more advanced method (Horton infiltration) is presented. This includes a time depended reduction of the rainfall input. By subtracting the hydrological losses (depression storage, wetting loss and soil infiltration) with the rainfall input, the residue corresponds to the contribution to the sewer system. Depression storage and wetting loss (combined as initial loss in the hydrological reduction factor model) are the hydrological losses in the beginning of a rainfall event, and is therefore considered constant in time. In the Horton infiltration method, the infiltration capacity is decreasing as a function of soil saturation. If the rainfall intensity exceeds the infiltration capacity of the soil, a runoff contribution is implemented (Horton 1939, 1940 and Chow 1964):

$$f_{cap,i}(t) = f_{end,i} + (f_{start,i} - f_{end,i}) \cdot \exp(-a_i \cdot t) \quad (5.1)$$

$f_{cap,i}$  is the infiltration capacity (m/s) for the area type  $i$ ,  $f_{start,i}$  and  $f_{end,i}$  are start and end infiltrations (m/s) respectively,  $a_i$  is the Horton exponent and  $t$  is the time.

The infiltration can be implemented in several ways and with different complexity. The simplest method is to apply an average infiltration to the sub-catchment, without distinguishing between the different area types. A more advanced method is to divide the sub-catchment into different parts categorized according to the permeability and/or surface slope in order to model the infiltration more accurately. For example, the infiltration model can be divided in pervious, semi-pervious and impervious surfaces. As with other models, the advanced method contains more parameters hence a larger risk of parameter uncertainties. In addition, the infiltration models can be combined with modelling of soil water content and groundwater level in order to calculate the dependence of these factors regarding the infiltration. This is known as a so-called RDI model (Rainfall Dependent Infiltration) (DHI, 2003a). Using this model, it is possible to simulate infiltration to the soil and, using the ground water level, simulate infiltration/exfiltration to the drainage system (see section 7.3). A RDI model can also include calculation of evaporation and the resulting deduction in runoff volumes. This, however, is often neglected due to negligible evaporation in temperate non-arid climates, which indeed is the case in the present study.

### 5.3.1 Choice of hydrological model

In order to determine which of the described sub-models are more suitable in the Frejlev catchment, in terms of number of parameters, parameter assessment, and complexity, a hydrological calibration (i.e. only based on volumes - not temporal variations), using approx. 350 observed rainfall-runoff events from the Frejlev catchment is applied. The method is described in detail in Paper III. The calibration is initially carried out by linear regression of the observed runoff depths (i.e. runoff volume divided by the impervious area) and the observed rainfall depth per event. Hereby, the two parameters, the hydrological reduction factor and the initial loss, can be estimated, as done in Paper I, Paper II, and Appendix C. Using a deterministic MOUSE model setup, a manual calibration of eight parameters in the Horton infiltration model is performed on the basis of the initial calibration. Doing this, it is possible to calibrate so that the two models predict the same runoff volumes in the mean,



and by adjusting the infiltration capacity on the semi-pervious surfaces it is possible to get the Horton model to predict a larger runoff volume during high intensity rainfall. This supports the basic hydrological theory that semi-pervious and pervious surfaces will contribute to the runoff if the rainfall intensity exceeds the infiltration capacity of the soil (See Figure 2 and 3, Paper III)

In order to investigate this further a more detailed analysis of the corresponding rainfall-runoff observation data is conducted in Appendix C. Basic hydrological theory states that the runoff should be larger if the water content in the soil is large. Because of this theory, a separation between rainfall events with a dry weather period of more and less than 24 h has been introduced. However, no significant difference concerning the runoff was observed (Figure 5.2).

With the purpose of investigating whether a larger runoff can be observed for high intensive rainfall events, a separation between high intensive events and low intensive events is presented in Appendix C. Due to the contributions from the semi-pervious and pervious surfaces, it was expected that the runoff would increase for high intensive events. The results, however, show the exact opposite (see example in Figure 5.3). It is the author's conviction that this has to do with that fact that the rainfall is assumed to be uniformly distributed spatially over the catchment, and high intensive events tend to be very local. Therefore, the rainfall depth will be under-estimated and the results show a larger runoff than is actually the case.

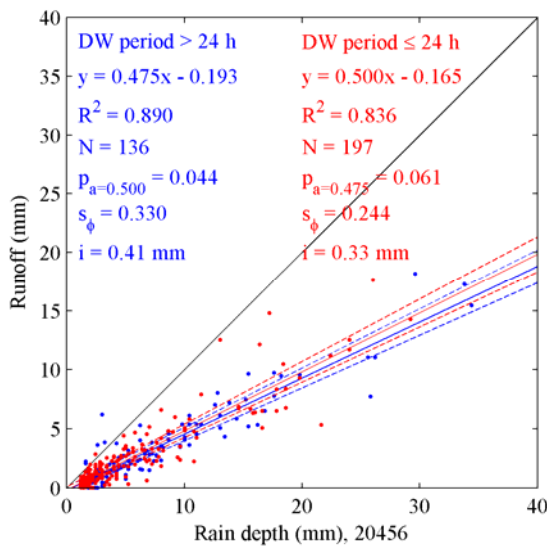


Figure 5.2 Corresponding measurements of runoff and rain in gauge 20456 with separation between events with dry weather (DW) period less and more than 24 hours before the rain starts.

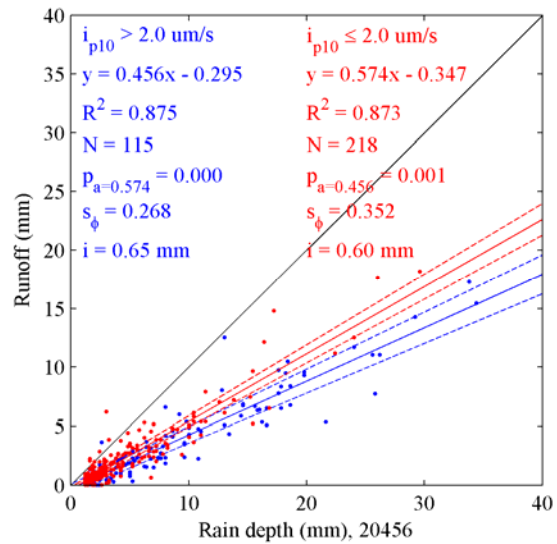


Figure 5.3 Corresponding measurements of runoff and rain in gauge 20456 with separation between events with high rainfall intensities (> 2 μm/s) and low rainfall intensities (≤ 2 μm/s)

As a result of no significant correlation between the rainfall intensity and the runoff, and therefore between the rainfall intensity and the soil infiltration, it is chosen to neglect this relationship in the thesis. The simple linear relationship between rainfall and runoff (the hydrological reduction factor model) is consequently applied in Papers IV - VII.

In general, the hydrological runoff model is a very essential part of urban drainage modelling. There are large differences with regards to whether the model is calibrated or not, especially if the model is un-calibrated. This must be considered one of the most uncertain parts of an urban drainage model (e.g. Arnbjerg-Nielsen 1996a, 1996b)

#### 5.4 Hydraulic surface runoff model

A surface runoff routing model predicts the transportation of water from the surface to the drainage system, i.e. input time series to every manhole in the drainage system. As it is the case with the other sub-models mentioned, the surface routing can be implemented with different complexity, e.g. as a Time-Area Model, a Kinematic Wave Model (non-linear reservoir), a Linear Reservoir Model, a Unit Hydrograph model, or by more complicated two dimensional models (using Kinematic Wave or the Fully Dynamic Wave approach). (Winther et al. 2006 and DHI 2003b).

The Time-Area Model is based on constant concentration time on each sub-catchment, so that the runoff is constant when the whole catchment contributes to the runoff. The concentration time is most often estimated as a global parameter, so that the same value is applied for all sub-catchments. Normally a rectangular catchment shape is assumed leading to the following equations:

$$Q(t) = i(t) \cdot F_{red,i} \cdot \frac{t}{t_c} \quad t \leq t_c \quad (5.2)$$

$$Q(t) = i(t) \cdot F_{red,i} \quad t_c < t \leq t_d \quad (5.3)$$

$$Q(t) = i(t) \cdot F_{red,i} \cdot \left(1 - \frac{t - t_d}{t_c}\right) \quad t > t_d \quad (5.4)$$

$Q$  is the discharge,  $i$  is the rainfall intensity,  $F_{red,i}$  is the reduced area on sub-catchment  $i$  (*impervious area multiplied by the hydrological reduction factor*),  $t$  is the time,  $t_c$  is the concentration time, and  $t_d$  is rainfall duration. An example of the Time-Area model using a concentration time of 7 minutes and rainfall duration of 20 minutes is presented in Figure 5.4.

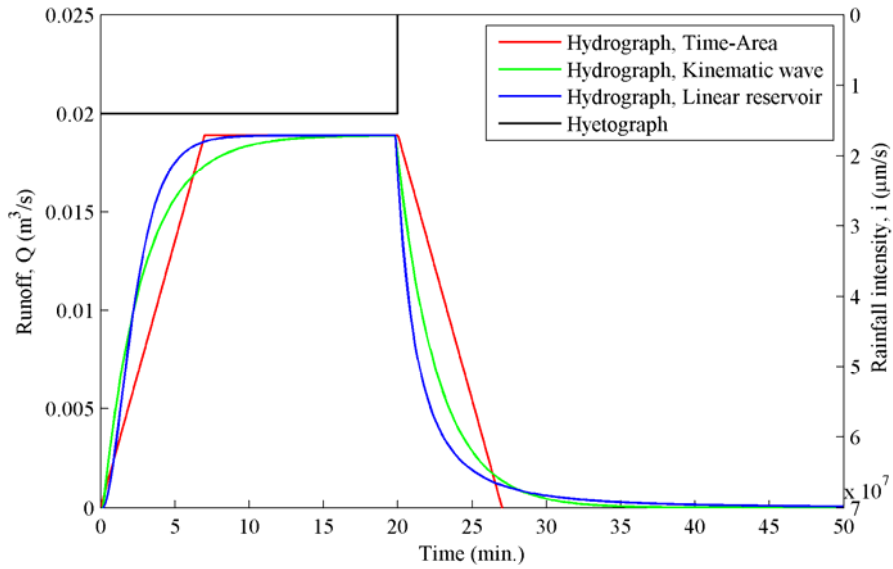


Figure 5.4 Example of the Time-Area model, the Kinematic Wave model and the Linear Reservoir model with arbitrary parameters.

Another type of hydraulic surface runoff model is the one dimensional Kinematic Wave Model (non-linear reservoir). Contrary to the Time-Area Model, the Kinematic Wave Model predicts the flow velocity on the surface depending on the water level by combining a continuity equation with the Manning equation (Winther et al. 2006 and DHI 2003b):

$$i_{eff,i}(t) \cdot F_i - Q_i = F_i \cdot \frac{dy}{dt} \quad (5.5)$$

$$Q_i = C_{b,i} \cdot y^{\frac{5}{3}} \quad (5.6)$$

$$C_{b,i} = M_i \cdot b_i \sqrt{S_t} \quad (5.7)$$

$$b_i = \frac{F_i}{L} \quad (5.8)$$

$i_{eff}$  is the effective rainfall intensity,  $F_i \cdot \frac{dy}{dt}$  is a storage term,  $M_i$  is the Manning number,  $F_i$  is the area of sub catchment  $i$ ,  $y$  is the water level (constant over the entire area),  $S_t$  is the terrain slope, and  $L$  is the catchment length. The indices  $i$  indicate one of the five area partitions, which must be specified in MOUSE. This approach is also applied by Wangwongwi-roj et al. (2004). An example of the kinematic wave model is shown in Figure 5.4 using a lumped calibration coefficient,  $C_b = 500 \text{ m}^{4/3}/\text{s}$ .

Similar to the kinematic wave model is the linear reservoir model in which the same continuity equation can be applied (equation 5.5). The only difference is the definition of the momentum equation (DHI 2003b):

$$Q = C_c \cdot y \quad (5.9)$$

$$C_c = F/T_L \quad (5.10)$$

$T_L$  is a catchment specific lag time. An example of the linear reservoir model is presented in Figure 5.4, using a value  $C_c = 50 \text{ m}^2/\text{s}$ .

Using a one dimensional routing model, is an obvious approximation to reality, as the overland surface water flows in two dimensions. This is a clear indication of model methodological uncertainty. The models presented must be specified with characteristic catchment lengths, slopes, roughness, etc, which must be considered highly empirical, when modelling two dimensional flow in one dimension. Furthermore, often only the main drainage system is simulated, which causes the surface routing model to account for both surface runoff and runoff in smaller service pipes leading to the main system (see Chapter 6). This generates commensurability errors (Beven 2008), as it is hard to determine combined parameters, with no physical meaning, for both pipe flow and overland surface flow. The surface routing model is rarely calibrated individually, since measurements of surface runoff are hardly ever conducted, except e.g. Spaangberg and Niemczynowicz (1993). However, some authors have calibrated urban drainage models of whole urban catchments, e.g. Clemens (2001) and Wangwongwiroj et al. (2004).

#### 5.4.1 Choice of runoff model

In Paper III a long term sensitivity analysis applying the presented surface runoff models is presented. This analysis clearly shows that there is an infinitesimal difference between the extreme statistics of CSO volumes and some difference on maximum water levels. However, to investigate the choice of runoff model on a smaller scale, the GLUE methodology is used to determine if the Kinematic Wave sub-model predicts observed flow time series better than the Time-Area Model (Paper VI). This is in fact the case as significantly higher likelihoods of goodness of fits are observed using the kinematic wave model. It is also obvious, examining Figure 5.4, that both the Kinematic Wave Model and the Linear Reservoir Model have longer tails. This seems more realistic studying observed flow time series. However, as it is primarily the hydrograph peak value that is important to the water level prediction and the runoff volume (area under the hydrograph) that is deceive for the overflow volume, the long term statistics do not change significantly with changing surface runoff model. Thus, the Time-Area Model is used in the Papers IV, and VII.

## 5.5 Hydrodynamic model (pipe flow model)

A hydrodynamic drainage model is based on the one dimensional Saint Venant equations, which are derived from the law of conservation of mass (Schaarup-Jensen 2002 and Sjöberg 1976):

$$\frac{\partial Q}{\partial x} + b \cdot \frac{\partial y}{\partial t} = q \quad (5.11)$$

$Q$  is the discharge,  $x$  is the flow axis,  $y$  is the water depth,  $b$  is the width at the water surface,  $t$  is the time, and  $q$  is the infiltration/exfiltration discharge per pipe meter. Furthermore, the Saint Venant equations consist of the law of conservation of momentum (second law of Newton), (Schaarup-Jensen 2002 and Sjöberg 1976):

$$\frac{\partial Q}{\partial t} + \frac{\partial \left( \frac{Q^2}{A} \right)}{\partial x} + g \cdot A \cdot \frac{\partial y}{\partial x} = g \cdot A \cdot S_0 - g \cdot A \cdot S_f \quad (5.12)$$

$A$  is the cross section area,  $g$  is the gravitation,  $S_0$  is the bottom line slope and  $S_f$  is the friction slope.

The Saint Venant equations can be used with different complexity: (1) as a kinematic wave model in which local and convective acceleration terms as well as the wave damping are neglected; thus the Kinematic Wave approach does not handle back water effects; (2) as a diffusive wave model in which local and convective acceleration terms are neglected; and (3) as a fully dynamic wave model, accounting for all terms in equation 5.12.

The two Saint Venant equations can be solved in different ways. In MOUSE it is done by a 6-point Abbott Ionescu finite difference scheme and a double sweep algorithm (DHI 2003a).

All setups in this thesis apply the dynamic wave model, as it contains the smallest numerical errors. The uncertainty of the hydrodynamic pipe flow model is not considered as it is expected to be insignificant.

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## Chapter 6

# Physical structure and conceptual uncertainty

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*This chapter presents the physical structure of an urban drainage model as well as the associated uncertainties and definitions of the conceptual uncertainty.*

### 6.1 Physical structure

In this thesis the physical structure is defined as parameters which are specific to the catchment, contrary to the calculation parameters which are generally applicable. Examples of the physical structure are pipe geometry, pipe slopes, geometry of weirs, gates, retention basins, surface geometry, pump characteristics, choker valves characteristics, QH-relations, etc. These parameters mostly found in technical maps, drawings, etc., and implementing them in an urban drainage model, the modeller will have to trust their accuracy. They are rarely questioned, i.e. hardly ever calibrated, randomized, or in other ways changed. However, the uncertainty of the physical structure can be reduced by an increase in the level of detail, e.g. by implementing all service pipes to the model, instead of only modelling the main drainage system. In special cases in which the technical maps, parts lists, etc. are very defective or insufficient the modeller might consider implementing these errors stochastically, but in the Frejlev case, this has not been necessary.

Several authors, e.g. Willems (2000b), Walker et al. (2003) and Beven (2008) do not distinguish between physical structural parameters and calculation parameters, but since there is a difference in handling the two types of parameters, it seems reasonable to define them as two. Obviously, there are overlaps with the calculation parameters depending on models setup of the system in question.

Another important part of the physical structure uncertainty is the inconsistency between the data used for model setup and the actual system. By use of TV-inspections, Faldager (2005) has presented numerous of these inconsistencies, e.g. displaced joints in pipes, open joints, ingrown roots, wrong coupling of pipes, production errors of pipes, cracks, corrosion of pipes, blocked pipes, large amounts of sediment, etc. Besides the drainage system one can think of phenomena such as local diversion of rainwater, local recycling of water, etc., which does not appear on the technical maps or drawings, and therefore presents an inconsistency, between the model setup and reality.

In general, it is difficult to handle these types of uncertainties statistically, and if the uncertainties must be quantified and reduced, investigations of the system in question must be conducted, e.g. by TV-inspections or detailed surveys. As the uncertainty can not be parameterized, the uncertainties with regards to the physical structure are ignored in the present study.

With regards to specification of the runoff area, the impervious area (or impervious percentage) is specified as part of the physical structure and hence kept fixed in stochastic simulations. On the contrary the hydrological reduction factor is defined as a calculation parameter, which is calibrated and/or randomized.

## 6.2 Conceptual uncertainty

The conceptual uncertainty primarily has to do with uncertainties originating from the choice of model or sub-models (basically the theory and physical laws applied), as well as discretisation of the drainage system and characterisation of parameters and processes in terms of spatial and temporal distribution. Therefore, as presented in the pentad (Figure 4.1), the conceptual uncertainty consists of both physical structure and model methodology uncertainty.

The discretisation of a drainage system is important in setting up an urban drainage model. Traditionally, only the main and the submain pipes are modelled, leaving out the branches from the individual houses. The surface runoff models must therefore contain a combination of surface runoff from roofs, lawns, paved areas, etc. and pipe flow in the branches to the submains. As described in Chapter 5, some surface runoff models apply a constant velocity (or concentration time). If this value must be representative for both surface and pipe flow, it is the author's opinion that it should not be seen as a physical parameter, but more as a calibration factor. Models based on calculation of velocity, assume constant values of e.g. slope and the roughness of the surface, and therefore the problem is the same. One could ask, why not just model all the pipes and surfaces separately, instead of combining the flow on the individual cadastral areas as one? The main reason is that you introduce several more parameters and physical structure and probably more errors are introduced compared to simplifying the model setup. Moreover, it can be difficult to acquire correct information of pipe dimensions and surface areas as the cadastral areas are private contrary to the mains and submains that are most often public (administered by the municipalities in Denmark).

In a general modelling context, an urban drainage model, as the one presented in this study, would be characterized as a spatially distributed model (Beven 2008). However, having a closer look at each of the pentad branches, it is clear that not all of these can be characterized as fully distributed. For example, the pipe roughness is in some conceptual model setups considered a lumped parameter as it is assigned to each pipe class (concrete, plastic, etc.). On the other hand the physical structure of the pipes (levels, slopes, diameters, etc.) is indeed based on local values for each pipe section, i.e. characterized as fully distributed. This is another important reason why the physical structure and the calculation parameters are separated in this study. By making each process or parameter more distributed, instead

of lumped, the conceptual uncertainty will decrease and vice versa. However, by increasing the level of detail by doing a more spatially distributed model setup, the uncertainty will shift from conceptual uncertainty to either input uncertainty or calculation parameter uncertainty instead.

In Paper VI and Chapter 7 the spatially distributed rainfall input is discussed further, and a discussion of spatial variability of individual parameters is presented in Chapter 8.





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## Chapter 7

# Input data uncertainties

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*The following chapter presents the uncertainties related to the model input data and boundary conditions. Especially the uncertainties related to the rainfall input are extensively covered.*

The main data inputs to an urban drainage model (for a combined sewer system) are the precipitation input and the dry weather flow (DWF). In some cases infiltration/exfiltration to/from the sewer system are included as input as well. The inputs differ from calculation parameters as they can vary in both space and time, and there are numerous levels of details concerning them. Inputs are not considered calibration variables, but can to some extent be randomized.

### 7.1 Rainfall input

Rain is a stochastic phenomenon and presents a spatial and temporal heterogeneity. The rainfall quantification is essential in urban runoff modelling, and the rainfall input is consequently considered one of the most uncertain parts of storm water modelling. In the vast majority of model setups for non-research purposes the rainfall is considered to be uniformly distributed over the entire catchment of the drainage system in question, i.e. either as synthetic rain or historical point measurements from rain gauges. As the synthetic rainfall also relies on observations which are statistically processed, the next section presents uncertainties with regards to measuring high temporal resolution rainfall. Several authors have investigated rainfall input requirements for urban drainage models, e.g. Vaes et al. (2001), Schilling (1991), Einfalt et al. (2004), Berne et al. (2004), and Rauch et al. (1998).

#### 7.1.1 Rainfall measurements

Whether modelling with real measured time series or design storms, the data is based on observations, and these observations obviously contain some uncertainties. In Denmark, the official rain gauges are all tipping buckets of the Rimco type (DMI 2004, 2006, 2007; Spildevandskomiteen 1999, 2006), and therefore the only type of rain gauge presented.

Several authors have investigated errors in sampling with tipping buckets, e.g. Fankhauser (1998), Habib et al. (2001), and La Barbera et al. (2002). These authors all identify problems with time scaling of the tipping bucket. The bucket tips for every 0.2 mm of rain

(Rimco gauge), and the intensity is calculated by distributing the 0.2 mm over the period of time between the tips. Thus, a temporal averaging occurs. However, this is only a problem during low intensities which are not considered to be interesting concerning neither maximum water levels nor combined sewer overflows. Furthermore, if the time scale is less than the transportation time in the drainage system, the errors are averaged in the drainage model, and will therefore not influence model results in modelling with real time series.

Furthermore, several authors e.g. Habib et al. (2001), Fankhauser (1998), La Barbera et al. (2002), Vejen et al. (1998), Vejen (2002), Overgaard et al. (1998), Allerup et al. (1997), and Stransky et al. (2007) indicate that the greatest uncertainty of sampling using tipping buckets is caused by local wind conditions. As the official Danish rain gauges are raised 1.5 m from the ground, local turbulence around the gauges causes the bucket to fail to catch the rain. This is especially a problem at low rainfall intensities and when large wind speeds occur (Appendix A). The problem is larger if solid precipitation is sampled, but this is not of any concern in the context urban drainage, due to the delay in the runoff. It is possible to correct observed rainfall data for local wind conditions (Allerup et al. 1997; Vejen et al. 1998; and Vejen 2002, 2005), but this requires reliable and local wind data, which is not available in this case. Any correction of data might cause new uncertainties. It is, however, not expected that the missing correction of data influences the runoff calculations in any way, as it is only a major problem during extreme wind conditions, and low rainfall intensity. These issues are discussed in Appendix A. Furthermore, doing calibration of a model applying the hydrological reduction factor, the error of the wind effect will implicitly be accounted for in the calibration.

In order to investigate the rainfall recordings in the three gauges closest to the Frejlev catchment, scatter plots of rainfall event depths are shown in Figure 7.1 and 7.2. It is evident examining the figures that gauge no. 20456 (Frejlev South) has recorded approximately 10 % more than the two other gauges in the period 1998 - 2006. Examining the periods from 1998 - 2004 and 2004 - 2006 individually, Appendix A, Figure A.12, it is observed that the bias is not present in the period from 2004 - 2006. Gauge 20456 was exchanged during January 2004. Whether the change in bias is due to the replacement of the gauge or due to a change in local wind conditions around the gauge (due to growth of the surrounding trees) is not investigated any further. Besides the bias a quite remarkable scatter is also present. The diagonal distance between gauge 20456 (Frejlev South) and 20458 (Frejlev North) is 1.2 km, and the mean standard deviation between the residuals is 0.8 mm, so even within this relatively short distance a spatial variance of the rain is observed. Between 20456 and 20461 (Svenstrup) the mean standard deviation is 1.1 mm (distance 3.8 km). It is evident that the greater the distance between the gauges the larger the standard deviation. As an attempt to use this correlation between the distance and the standard deviation (or correlation coefficient) to predict a general correlation length between gauges, Figure 7.3 is obtained by comparing rainfall events from nine gauges in the municipality of Aalborg (Appendix B). Ideally, this plot might limit the distance in which the gauges are no longer correlated, by applying two approaches, the Gaussian fit (based on Willem's 2001) and a linear fit. Obviously a correlation is present, but there is a great extent of uncertainty.

It is, however, reasonable to conclude that within a distance of 30 - 60 km the observations are independent (on average). The approach is fully presented in Appendix B.

Several authors have investigated the spatial extent of rainfall events, e.g. Schilling (1991), Berne et al. (2004), and Vaes et al. (2005). Vaes et al (2005) found similar results regarding the correlation length, applying a well-calibrated spatial rainfall generator.

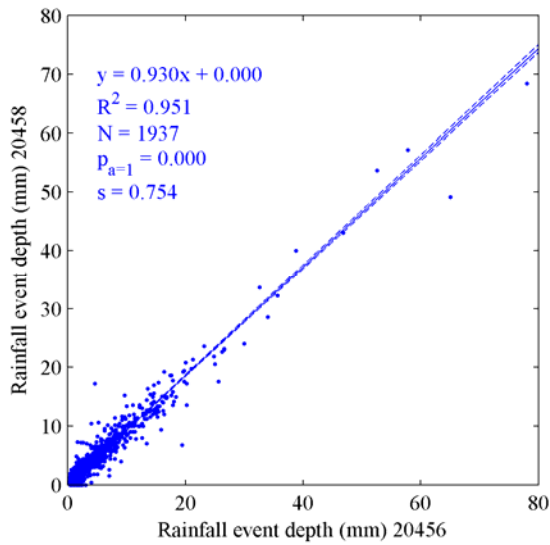


Figure 7.1 Rainfall event precipitation in 20456 vs. 20458 in the period 1998-2006.

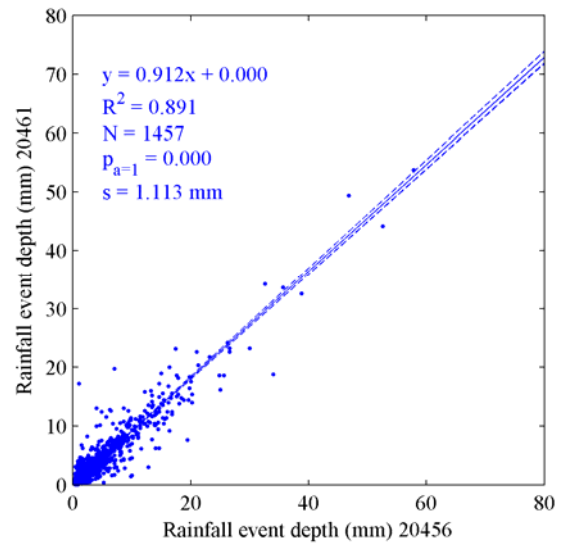


Figure 7.2 Rainfall event precipitation in 20456 vs. 20461 in the period 1998-2006.

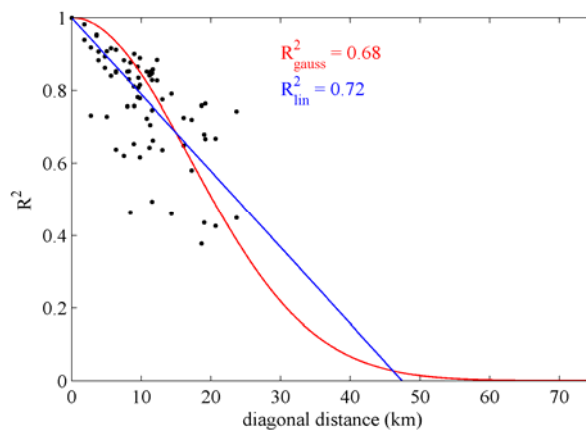


Figure 7.3 Correlation coefficients of rainfall depths and the diagonal distance between gauges. Summer data.

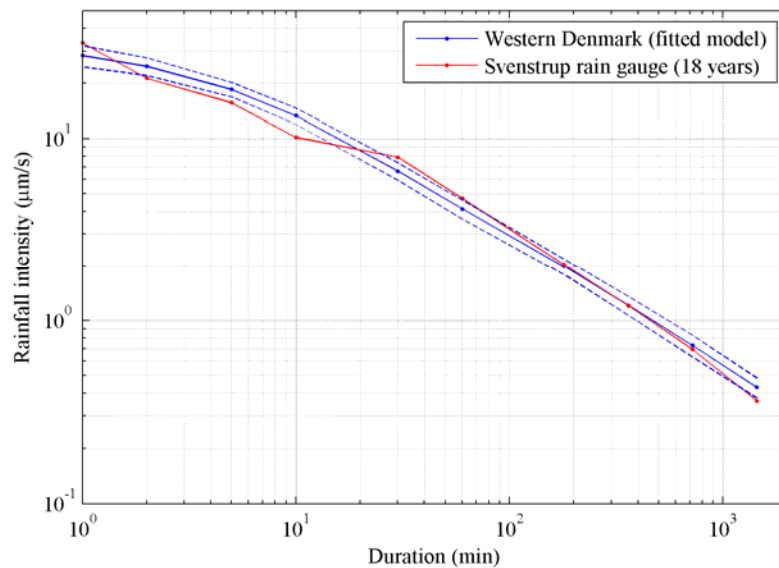


Figure 7.4 Example of IDF-relationships with a return period of 2 years from *Spildevandskomiteen* (2006) with 95 % confidence intervals and the *Svenstrup* rain gauge (no. 20461).

### 7.1.2 Modelling with design storms

Synthetic rain or design storms are based on many years of statistics of rainfall measurements, e.g. *Intensity-Duration-Frequency* curves (IDF-curves), (Spildevandskomiteen 1974, 1999; Mikkelsen et al. 1998; Vaes 1999; Willems 2000a; and Arnbjerg-Nielsen et al. 1998, 2002) See example in Figure 7.4. These can be used directly for design purposes, by e.g. the Rational Method or the Time-Area method. However, the IDF relationships can also be applied directly in an urban drainage model by simulating a given rainfall intensity with a given return period one at a time and examining the system response.

Another widely applied method is the Chicago design storm (CDS), (Kiefer & Chu 1957; Mikkelsen et al. 1998; Madsen et al. 1998, 2002; Arnbjerg-Nielsen et al. 2002; and Vaes and Berlamont 2002). This is also based on the IDF relationships, but using the CDS rain, the rainfall intensities and durations are combined to one event with a given return period, and the maximum water levels in the drainage system are predicted for different rainfall intensities with different durations within one simulation.

Modelling using a synthetic rainfall input, it is presumed that the return period of the rain is the same as the return period of the maximum water level (per event) for the sewer system in question. The uncertainties concerning synthetic rain data can be classified as conceptual uncertainties, as the data does not represent real rainfall events. As an example, a critical situation (e.g. local flooding) can occur when two rainfall events occur within a short period of time. This might be a crucial uncertainty of modelling with synthetic rainfall data, as this phenomenon is not included in modelling with synthetic rain. Moreover, synthetic rainfall data is often estimated for regional or national areas, neglecting local variations.

Neither the IDF-relationships nor the CDS rain is used as rainfall input in this thesis, as only maximum water levels and not combined sewer overflow volumes, can be predicted using these types of input.

In Paper IV and V, another approach using a synthetic rainfall input is applied. Based on Willems (2001) synthetic rainfall events with a truncated Gaussian shape are generated. Two-component exponential distributions are fitted to the variables known from the IDF-relationships, i.e. rainfall depths per event, event durations, and peak intensities per event. By sampling correlated values from these distributions it is possible to predict occurrence of combined sewer overflow (CSO) using the two characteristic variables, the rainfall event depth and the event duration. In prediction of CSO-occurrences, the peak intensity in the Frejlev sewer system is not important as the large retention basin fills up before CSO occurs. Any potential fluctuations in rainfall intensity are therefore smoothened out. The prediction of the maximum water levels is solely based on the peak intensity. This assumes the same correlation between peak intensity and maximum water levels as assumed using the Chicago Design Storm. However, in this case a Gaussian shaped rain is applied instead of a uniform block rain. Neither the rainfall depth nor the duration affects the water level remarkably and are not included. A uniform block rain is also tested but a better model fit was predicted using the Gauss shaped rain. Two examples of the Gauss shaped rain are shown in Figure 7.5.

The concept of this method is elaborated in Chapter 10.1 as well as in Paper IV and V. Another advantage, using this method, is the possibility for implementing uncertainties on the parameters. For example in Paper V, the uncertainty on the rainfall event depth is implemented by fitting the scatter of Figure 7.1 and 7.2 to a normal distribution with the purpose of incorporation the uncertainty by not applying a rain gauge located in the catchment. Moreover, the spatial variability of the rain is included as presented in Section 8.1.

### 7.1.3 Modelling with observed time series

Another type of rainfall input is modelling with real historical rainfall data from point measurements, in which long time series are employed in order to determine long term statistics, i.e. return periods of surcharge, flooding, or combined sewer overflow (Einfalt et al. 1998b; Mikkelsen et al. 2005; and De Toffol et al. 2006). Modelling with historical point measurements of rainfall is expected to be uncertain for three reasons: (1) uncertainty in measurement of the rain (as stated in section 7.1.1); (2) uncertainty of the return periods, i.e. whether the historical rain series is long enough to represent significant statistics; and (3) the geographical variation of the rain. With regards to the latter, it is well-known, that convection rain (thunderstorms) is lumped and has large spatial dispersion whereas stratiform rain (frontal rain) is more uniform. Due to this geographical variation, uncertainties occur when the rain is measured in a single point. In addition to this, a rain gauge is hardly ever situated in the catchment in question, and time series are rarely long enough for assessing long term statistics, forcing the modeller to use time series data originating from a rain gauge located elsewhere. In Figure 7.6 an example of three rainfall time series is shown. It is evident comparing the time series that, both start and end times of the events are different. Moreover differences in depths and intensities are present.

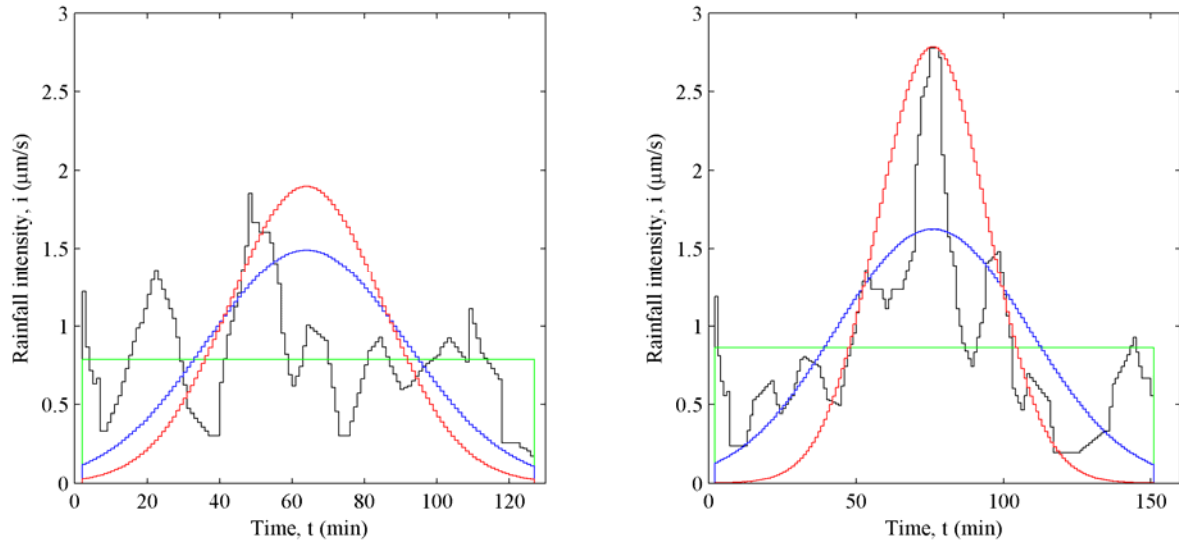


Figure 7.5 Examples of Gauss shaped rain based on the 10 min. event peak intensity (red), Gauss shaped rain based on rainfall event depth and duration (blue), observed rain series - averaged over 10 min. (black) and an average intensity uniform block rain (green)

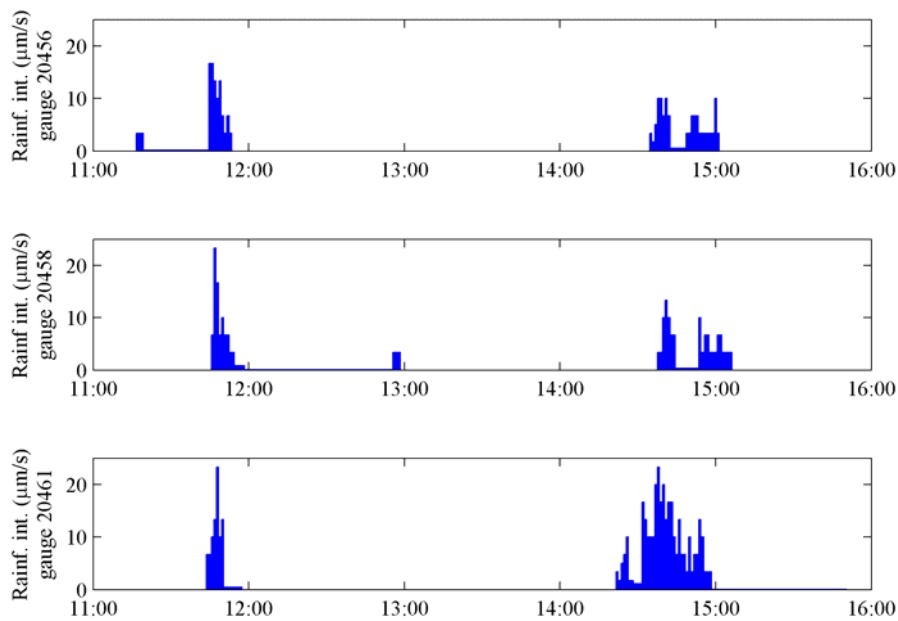


Figure 7.6 Example of three observed rainfall time series. June 4, 1999. The Frejlev South gauge (no. 20456) and the Frejlev North gauge (no. 20458) both have recorded an accumulated depth of 13.2 mm. The Svenstrup gauge (no. 20461) has recorded 25.0 mm.

Dealing with uncertainties by randomisation of parameters is a difficult task when modelling with real historical time series, as the randomisation would have to be non-stationary. It is also a question of time scaling - should the randomisation be applied on the rainfall intensities with a one minute temporal resolution or should some auto-correlation be applied? Kuczera et al. (2006) has done this within the area of rainfall-runoff modelling on rivers, but as far as the author knows, it has never been applied in urban drainage.

In this thesis it is selected to use the historical rain series without any correction, change or randomisation (Paper II, VI, and VII).

In Paper VI a comparison between modelling with recorded time series from one rain gauge and modelling with a spatial average of two gauges is presented (both uniformly distributed over the catchment). Therefore, the prediction uncertainty is reduced by an increase in level of detail. By comparing likelihoods a better fit between model predictions and observed time series is found applying a weighted average of data from two rain gauges compared to modelling with data from only one gauge. Using averaged historical rain causes local differences to be reduced due to averaging. Another possibility would be to implement the two time series so that they cover two different areas in the model, i.e. as a semi-distributed rainfall input. This is, however, not considered in the present study. Whether the method of applying two gauges is applicable outside the Frejlev catchment is doubtful, as two rain gauges within the same small catchment are hardly ever seen.

The uncertainty due to the non-uniform spatial distribution of the rain is indirectly implemented as an uncertainty on the hydrological reduction factor (see Section 8.1). This uncertainty is, however, event-based and thus, any spatial and temporal variability within a run-off event is neglected. This might influence the prediction of flow time series to some extent as it is seen in Paper VI. However, analysing the extreme event statistics of surcharge, flooding, and CSO volumes, the differences in the temporal variations are found to be unimportant.

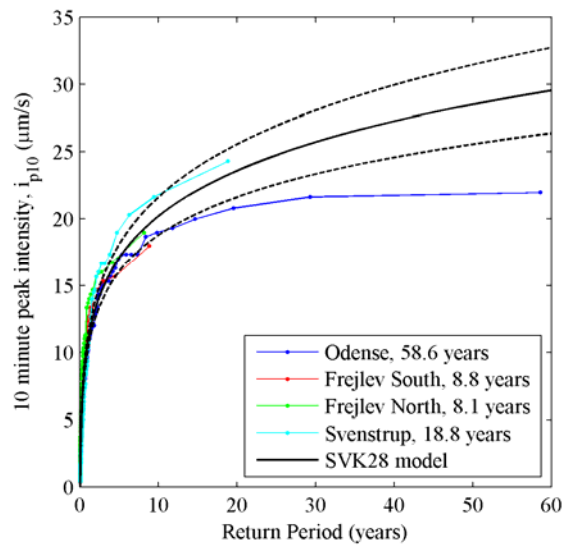
In Paper VII the same approach is applied. The object of the paper is to assess long term uncertainties on CSO-volumes and surcharge/flooding and an uncertainty contribution is applied on the return periods as well. This is elaborated in section 7.1.4.

#### 7.1.4 Return period uncertainty

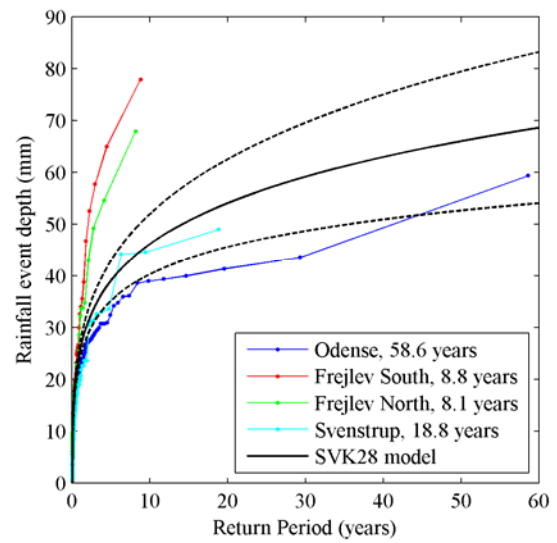
In Paper VII the return periods of maximum water levels and CSO volumes are estimated applying return periods of the rainfall event peak intensities and depths. The methodology is explained further in the paper and Chapter 10.3. The return periods of the intensities and depths are estimated applying a fitted Generalised Pareto model (Madsen and Rosbjerg 1997a, 1997b; and Mikkelsen et al. 1998), which is based on measurements from 66 Danish rain gauges in the period 1979 – 2005 (Madsen and Arnbjerg-Nielsen 2006; and Spildevandskomiteen 2006).

The statistics presented in Spildevandskomiteen (2006) have resulted in a division of the Danish rainfall statistics in two regional zones, one for the Western part of Denmark and one for the Eastern part. Using the accumulated yearly precipitation, a local estimate of the return period uncertainty can be calculated. Figure 7.7 presents the 10 minute peak intensity estimated by the Pareto model and local observations, and Figure 7.8 presents same but showing the rainfall event depth.





*Figure 7.7 Return periods for the 10 minute peak rainfall intensity, using reel measured data and the Pareto model (SVK28)*



*Figure 7.8 Return periods for the rainfall event depth, using reel measured data and the Pareto model (SVK28)*

It is evident in both figures that the return periods estimated in the local series does not fit completely within the 95 % confidence interval of the Pareto model. This is due to the relatively short measuring period. Willems (2000b) has stated that statistically reliable return periods can only be assessed corresponding to 10 % of the rain series length. Using this definition the observed data fit quite well within the confidence bands of the Pareto model.

In order to reduce this uncertainty, the return periods of the Pareto model are applied in Paper VII, by estimation the mean return period and confidence interval of the Pareto model corresponding to the value of the local event value of either rainfall peak intensity or depth. It is then possible to generate return periods applying a triangular distribution with the two confidence values and the mean. If, for example, a rainfall event depth of 40 mm is observed in the Svenstrup rain series, the traditional ranking methodology to assess the return period would equal 5.7 years. However, if the Pareto model is applied, the mean value equals 5.5 years and the 2.5 % and 97.5 % confidence bands equals 3.8 years and 9.6 years respectively.

As the statistics of the Pareto model are based on a very large dataset, the estimated return periods are considered much more reliable compared to the local return period estimates.

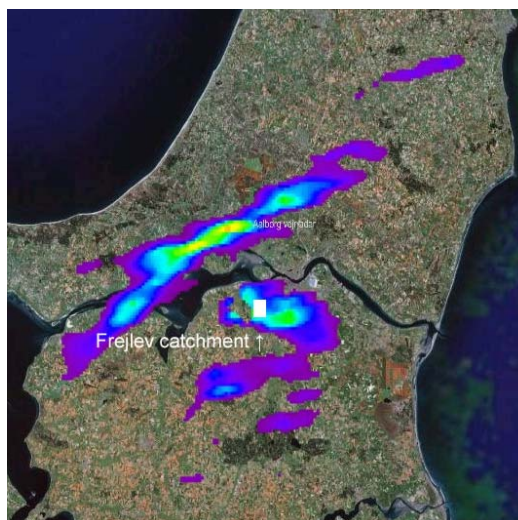
#### 7.1.5 Modelling with spatially distributed rain

Increasing the level of detail further, the rainfall input can be modelled as fully temporally and spatially distributed rainfall, e.g. by assessing a different time series to each sub-catchment. This can be implemented by use of rain data from several rain gauges situated inside and outside the catchment applying a geostatistical interpolation model, e.g. Kriging (Matheron 1963). This would, however, require a very large number of rain gauges, and as

far as the author knows it has never been researched in the context of urban drainage but only on larger scales within rainfall-runoff modelling of rural catchments.

Another possibility of implementing a spatiotemporal rainfall input is by applying data from weather radars in which the rainfall is discretized in individual rain cells or radar pixels in a mesoscale area. (Einfalt et al. 2004; Pedersen et al. 2005; Rasmussen et al. 2008b, Kramer et al. 2005, Smith et al. 2007; Rasmussen and Siggaard 2006; Vieux and Bedient 2004; Smith et al. 2007; and Berne et al. 2004). The use of weather radar data in urban storm water drainage is currently researched diligently, and it is the author's conviction that use of weather radar data is not used for non-research purposes - at least not yet. The uncertainties are still numerous and not discussed in this chapter. Figure 7.9 shows an example of weather radar data from Aalborg Weather Radar with quite large spatial variability in this specific event. Even though weather radar data might be very applicable in prediction of flooding in the future, current time series are still rather short and therefore not applicable for prediction of long term statistics.

Spatiotemporally distributed rainfall can as another possibility be produced synthetically and implemented using a rainfall generator or rainfall model. Willems (2001) has calibrated a 2D-Gaussian shape rainfall generator, using a large number of rainfall events. This generator is applicable on both small and large scales, i.e. for both rural and urban rainfall-runoff modelling. Several other investigations have been conducted using synthetic spatiotemporal rainfall e.g. Einfalt et al. (1998a), Vaes (1999), Vaes et al. (2005), Willems (1999, 2001), Willems and Berlamont (2002), Luyckx et al. (1998), and Vaes et al. (2001). The uncertainties using a rainfall generator are to a great extent dependent on how well the generator is calibrated and how well the generator can describe the stochastic phenomena of precipitation - especially in prediction of extremes. The uncertainties with regards to applying a rainfall generator would be characterised as model methodological uncertainties, cf. the pentad (Figure 4.1).



*Figure 7.9 Example of radar data from Aalborg Weather Radar. The extent of the figure is approx. 100 x 100 km*

In the present thesis, the spatiotemporal methods are not investigated as it is the author's conviction that the Frejlev catchment is too small to benefit from a fully distributed rainfall input (see Figure 7.3 and 7.9). It would, however, be interesting to investigate some of the spatiotemporal methods in order to compare modelling with data from one or two rain gauges as presented in section 7.1.3.

#### 7.1.6 Uncertainties due to climate changes

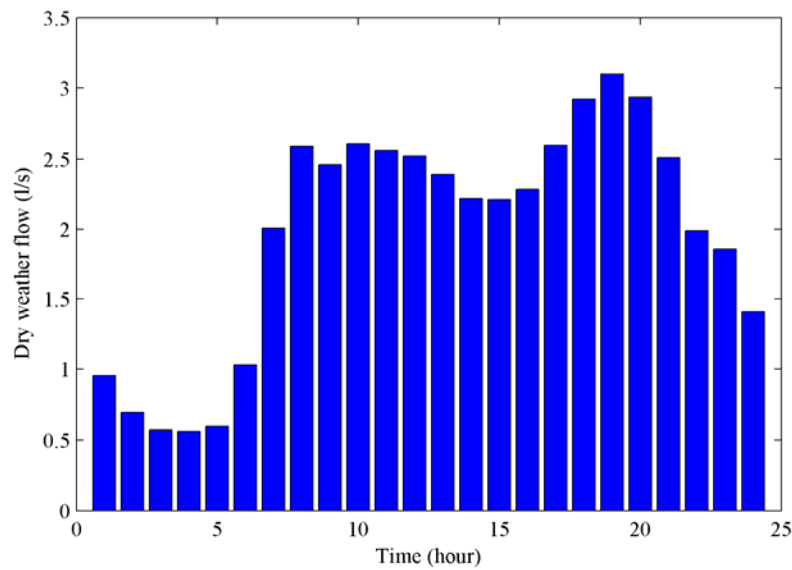
Another uncertainty related to the rainfall is the question of climate changes. When using long time series for hindcasts of urban drainage systems, it is presumed that the frequencies of extreme rainfall intensities and volumes are valid for the future as well, but if climate changes generate more frequent extreme rainfalls with larger intensities and volumes, this assumption must be rejected. Arnbjerg-Nielsen (2005) has shown statistically significant trends towards more extreme and more frequently occurring rain storms in Denmark, and Grum et al. (2006) have shown that extreme precipitation events effect urban drainage and cause more frequent flooding as a result of climate change. It is important to state that the results are based on one regional climate model assuming one future scenario.

Uncertainties due to climate changes are, however, not considered in the present study due to the reasons explained in Chapter 2.

### 7.2 Dry weather flow

Apart from the rainfall input, the input data (or boundary conditions) also includes the Dry weather flow (DWF), which is the contribution from waste water flow in a combined sewer system. Generally the DWF constitutes a rather small percentage of the total flow during rain. Still it must be included in the total runoff from urban areas in order to maintain mass balance. This is especially important when the model in question is calibrated against measured flow data. Usually, the DWF in residential areas is distributed uniformly and assumed proportional to the number of inhabitants or person equivalents (PE). However if large point sources are present, such as industries, these must be handled separately. There are three levels of detail concerning the quantification of the DWF (increasing level of detail): (1) empirical estimation, based on literature values; (2) measurements of the water supply (the DWF is assumed the same as the water consumption) or (3) direct measurements of the DWF, e.g. through high temporal resolution flow measurements from a sewer system during dry weather (Schaarup-Jensen et al. 1998; Schaarup-Jensen and Rasmussen 2004). The temporal discretisation is also important with regards to uncertainties, i.e. if the DWF is assessed hourly or daily, or if weekdays are distinguished (Schaarup-Jensen and Rasmussen 2004) have shown a remarkable difference in DWF between weekdays and weekends in the Frejlev catchment)

With concern to the overall uncertainties of the DWF it is obvious that, the higher level of detail, (spatially and temporally), the less uncertainty, however it is important to keep in mind, that the DWF contribution to the total runoff during rain is most often rather limited.



*Figure 7.10 Mean diurnal flow variation based on 10 years of measurements in the Frejlev catchment.*

In the present study a fixed diurnal variation is assumed, as shown on Figure 7.10. In the deterministic modelling approaches (Paper II and III) the variation is applied as presented in the figure. In the stochastic approaches (Paper V, VI, and VII) the diurnal variations are fixed relatively as in Figure 7.10, and the total diurnal flow is randomized.

### 7.3 Infiltration/exfiltration

Infiltration/exfiltration to/from a drainage system are very uncertain parameters. Both depend on several factors, e.g. state and age of the drainage system, imperfections in the drainage system, ground water level, the types of soil surrounding the drainage system, water level in the system, etc. The infiltration and exfiltration are very difficult to quantify as they are mostly local phenomena. Infiltration to drainage systems can be estimated by investigating base flow measurements, e.g. at night when DWF is low. This type of investigation may be complicated considerably though, if exfiltration also occurs (Schaarup-Jensen and Rasmussen 2004). Several authors have investigated infiltration and exfiltration from sewer systems, e.g. Bertrand-Krajewski (2008), De Benedittis and Bertrand-Krajewski (2005a, 2005b), Vollertsen et al. (2002), and Vollertsen and Hvitved-Jacobsen (2003).

In Denmark, many houses in areas with high ground water level have local drains around each house in order to prevent infiltration to basements. Typically, these drains are connected to the separate waste water system, in case there is a separate system, otherwise the combined sewer.

Miljøstyrelsen (2000) has investigated infiltration to sewer systems in Denmark. According to data conducted from 755 different waste water treatment plants (WWTP) the mean infiltration from the sewer systems to the WWTP amounts to an estimate of 29 % of the DWF.

Vollertsen et al. (2002) and Vollertsen and Hvitved-Jacobsen (2003) have investigated ex-filtration from sewer systems by reviewing the literature on the topic, performing a pilot scale study and excavating a leaky sewer. Vollertsen et al. (2002) states that up to 25 % of the DWF may exfiltrate from the sewers.

The overall uncertainties caused by uncertain estimation of infiltration/exfiltration are difficult to quantify, as they constitute local phenomena, and are dependent on the state of the system in question.

The infiltration in the Frejlev catchment is not considered a problem, since ground water levels are low. Studying the flow at night Schaarup-Jensen and Rasmussen (2004) have shown that no considerable infiltration occurs (Figure 7.10), which is why infiltration input is neglected in this study.

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## Chapter 8

# Calculation parameter uncertainties

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*This chapter presents the different parameters and uncertainties related to the hydrological and hydrodynamic methodologies described in Chapter 5.*

Naturally the choice of model and model complexity is crucial to the number of calculation parameters included in an urban drainage model. For that reason, only selected parameters are described. The calculation parameters differ from the input data as they are not a boundary condition and are not varying temporally (however in some cases a variation from event to event is introduced). According to Lei (1996), calculation parameters can not be measured directly, but only estimated indirectly by analysis of measurements or experiments or by calibration. An optimal calibration with calculation parameters is only possible when the physical structure uncertainty and the model methodology uncertainty are minimal. The calculation parameters can easily be handled statistically e.g. by implementation of a specific probability distribution for each parameter. Thus, it is possible to randomize variables, e.g. by doing Monte Carlo Simulations

The following description of parameters is structured according to three sub model types: the hydrological surface model, the hydraulic surface runoff model, and the hydrodynamic pipe flow model.

### 8.1 Hydrological parameters

The choice of hydrological surface model is vital for the number of hydrological parameters. As presented in Chapter 5.3 two different approaches are applied in this study, namely the simple linear hydrological model based on the hydrological reduction factor and the more advanced Horton infiltration model. The linear model contains two parameters: the hydrological reduction factor and the initial loss, whereas an advanced model including infiltration can include up to 20 parameters (DHI 2003b), e.g. start and end infiltration, wetting loss and detention storage for different types of catchments. However, in Paper III, the number of parameters are reduced to 8, as the pervious surfaces are neglected. Obviously the advanced model is more difficult to calibrate, because of larger degrees of freedom and presence of equifinality (Beven 2006).

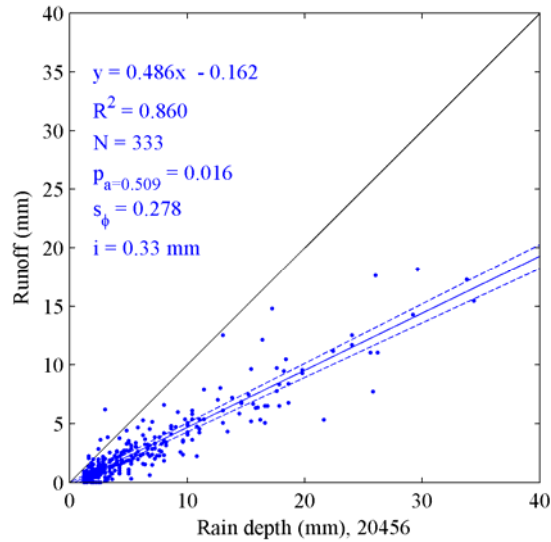
The Horton infiltration model is rejected in Appendix C due to no indications of runoff from semi-pervious and pervious surfaces in the Frejlev catchment (based on the flow recordings). Therefore, only the parameters contained in the simple linear model are presented.

Several investigations concerning choice of hydrological parameters have been conducted, especially concerning simple linear models, e.g. Arnbjerg-Nielsen and Harremoes (1996a), Choi and Ball (2002), Jensen (1990), and Miljøstyrelsen (1997), as well as in Paper I and II and Appendix C in this thesis.

In Appendix C and Paper I different approaches of estimating the hydrological reduction factor are applied based on corresponding measurements of rain and runoff from the Frejlev catchment. In these analyses the impervious areas are kept fixed (cf. the definition of the physical structural uncertainty) and the reduction factor is used as a ratio measure between the rainfall depth and the runoff from these areas. Figure 8.1 presents one of these analyses. Minor deviations in the reduction factor are observed depending on which rain gauge is used as input, but these are not significantly different statistically. In Paper II it is shown using results from Paper I, that calibration of a hydrological surface model is very important in order to get reliable results. The Frejlev catchment is analyzed with regards to surcharge and overflows, using a calibrated value of the hydrological reduction factor of 0.45 and compared with simulations, done with a hydrological reduction factor of 0.90, corresponding to standard literature values. (*The calibrated value of the reduction factor in the papers and in this chapter might vary a little due to an increase of observations during the study*). This corresponds to a doubling of water volumes using the first reduction factor compared to the second. Following this it is concluded that the hydrological reduction factor is very decisive for prediction of combined sewer overflow volumes and maximum water levels.

Moreover, quite a large dispersion centres the regression line. In fact, in some events a reduction factor larger than 1 is observed (corresponding to larger rainfall than runoff). The reason for these phenomena is that the rainfall (from one rain gauge) is assumed to be uniformly distributed over the catchment. If the accumulated event rainfall depth is larger elsewhere in the catchment than observations in the rain gauge, an underestimation of the rainfall is present. The dispersion is consequently an indication of the spatial rainfall variability. Fortunately, by assuming normal distributed residuals of the regression, the standard deviation can be used as a surrogate measure of the spatial rainfall variability, when using data from one rain gauge only as input to an urban drainage model (Paper V, VI, and VII). Applying this method does not lead to a distributed model, as the rainfall input is still applied uniformly over the catchment.

However, when doing Monte Carlo simulations and the whole distribution of the reduction factor is sampled and propagated through the model, the model outlet volumes will correspond to the observations, though some temporal variations upstream in the system may be ignored.



*Figure 8.1 Corresponding measurements of runoff and rain in gauge 20456 (Frejlev South). The regression line slope corresponds to the hydrological reduction factor and the cut off value on the abscissa is the initial loss*

Generally, the uncertainty of the hydrological sub model is very large, especially if the model in question is un-calibrated. Therefore, a randomization of the hydrological reduction factor and the initial loss is implemented in Papers V, VI and VII.

## 8.2 Hydrodynamic surface runoff parameters

As presented in Chapter 5.4 three different complexities of hydrodynamic surface runoff models are investigated in this study; the Time-Area model, the Kinematic Wave model and the Linear Reservoir model.

In Denmark almost every hydrodynamic surface model used by consulting engineers uses the Time-Area model with a constant and a globally determined surface runoff time, meaning that a lag time is applied regardless of the sub-catchment size. This is clearly a parameter uncertainty as sub-catchments vary in size and shape. However, Paper III has shown that modelling of surcharge, flooding, and CSO-volumes in un-calibrated urban drainage models are somewhat independent of the surface runoff time, as the uncertainties of the assessment of runoff volumes are several times bigger. Therefore, in un-calibrated, models the choice of model complexity becomes a minor uncertainty. On the contrary, the routing parameter determination can be decisive for accurately calibrated models.

The surface concentration time is sampled uniformly in both Paper V, VI and VII as it has not been possible in the present study to determine a higher probability with regards to one concentration time compared to another.

As explained in chapter 5.4, the Kinematic Wave model and the Linear Reservoir model are simplified so that the different surface parameters are lumped into a single calibration pa-



parameter. Therefore, the assessment of these parameters becomes purely empirical, and due to ignorance of these parameters these are sampled using a uniform distribution.

Generally, the parameters of the surface flow routing models are difficult to assess, as few have measured the flow from individual sub-catchments. As a result quite large sampling intervals are chosen for the individual parameters. Furthermore, as the parameters are more or less empirical, it is chosen not to implement any spatial distribution in the assessment, i.e. all parameters are randomized globally.

### 8.3 Hydrodynamic pipe flow parameters

The hydrodynamic calculation parameters considered in this study are the head loss in manholes and the roughness of pipes (or Manning number).

In the MOUSE model the head loss is assessed by a head loss shape coefficient ( $K_m$ ) which determines the shape of outlets from manholes, e.g. 0.25 for round edged outlets and 0.5 for sharp edged outlets (default values corresponding to DHI (2003a)). The head loss shape coefficient may be considered part of the physical model structure, but as the temporal variations in the sewer system are very dependent on the head losses (e.g. Wang et al. 1998) it is decided to include these as stochastic variables. Furthermore, it is decided to randomize the head loss by drawing fully correlated values for each outlet depending on whether the outlet is round edged or sharp edged. Moreover, no preferences are given to the distribution of the variables and therefore uniform distributions are applied.

Similar assumptions apply for the pipe roughness (the Manning number). This is also drawn fully correlated depending on whether the pipe material is plastic, smooth, normal, or rough concrete. The roughness in sewer systems might be quite large if sedimentation occurs (Mark 1995, Schlütter 1999, and Choi and Ball 2002). Therefore, it is decided to sample the Manning number normal distributed with quite large standard deviation.

Both Manning number and head loss are considered to be global parameters, even though there might be considerable local differences. Preferably, some correlation between the roughness in different pipes should be implemented, but as it is the author's conviction that this would have very little importance for both flow, as well as water level, this is neglected.

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## Chapter 9

# Observation data uncertainties

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*This chapter presents uncertainties related to the observation data which is used for calibration.*

The observation data is data which is used for calibration. For example flow measurements from a sewer system (Schaarup-Jensen et al. 1998), water level measurements, measurements of combined sewer overflows, etc. One could define the rainfall measurements as observation data as well, but these are presented in the rainfall input section (Chapter 7). Uncertainties regarding measurement data are difficult to specify generally, as they depend on how the measurements in question are conducted, but, as always with measurements, there is a probability of measuring errors, errors in data treatment, errors concerning the equipment, etc. It is important when using measured data for calibration, that the modeller is aware of different measurement errors, otherwise the calibration might be defective.

In this study the main observation data is the flow observations from the research and monitoring station in Frejlev. According to the specifications of the manufacturer, both flow meters function with a maximum flow rate error of 1-1.5 % and the meters are tested and calibrated to this error level. During the running period some problems especially with the 300 mm gauge have occurred. E.g. the meter has not measured the low flow under 2-3 l/s in the recent year, but no indications of errors during wet weather are present, and are not considered a problem. In addition, some other problems with the sampling computers and the data transmission equipment have been observed, causing no data to be available during these periods.

The overflow registrations conducted by the Municipality of Aalborg are based on an on-off switch in the CSO-structure and logs binary data every 4 minutes indicating if there is overflow or not. The data has been manually controlled by the Municipality of Aalborg, in order to remove potentially false registrations of overflow, and therefore it is believed that the uncertainty on defective data is rather low. Some temporal uncertainty might occur due to the resolution of 4 minutes, but this is not considered a problem.



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## Chapter 10

# Stochastic modelling approaches

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*This chapter presents a review of the stochastic modelling approaches which are implemented in this study to transform uncertainties on inputs and parameters to an uncertainty estimate of model predictions. The assumptions, methodologies, results and discussions are presented in detail in Papers IV-VII.*

Based on the methodologies, inputs, parameters, physical structure, observations, and the uncertainties related to these, different approaches are implemented in order to transform the uncertainties on input data and parameters to an uncertainty estimate of the model predictions. In this thesis three quite different approaches are investigated, however many other either analytical or numerical approaches could have been applied as well. The specific methodologies are presented in the Papers IV - VII, and this chapter will primarily present the differences in inputs, parameters, observation data, and the methodologies applied. Table 10.1 presents the three approaches in terms of model inputs, methodologies, etc. Some values and distributions of parameters may vary in the four papers, due to the progress and increase of knowledge during this study.

All three approaches are based on the MOUSE model with a stochastic shell programmed in MATLAB. The shell has been used to generate *ASCII* input files to MOUSE, so that the repeated simulations could run automatically. The post processing of results are also programmed in MATLAB.

The chapter presents selected results of the different approaches; the more specific results are presented in the papers.

*Table 10.1 Characteristics of the stochastic approaches*

Approach	Prediction of surcharge, flooding, and combined sewer overflow using reliability techniques and parameterisation of rainfall input (Chapter 10.1)	Event based stochastic time series calibration (Chapter 10.2)	Long term stochastic prediction of maximum water levels and combined sewer overflow volumes (Chapter 10.3)
Calibration	no	yes	no
Rainfall input	Synthetic events based on recordings from the Svenstrup rain gauge	6 historical events based on recordings from the Frejlev rain gauges	730 historical events based on recordings from the Svenstrup rain gauge
Method	FORM / MCIS / MCDS	GLUE	LTSMC
Sim. time (h)	2 / 4 / 25	10000	12000
Output	Occurrence of surcharge flooding, and CSO	Flow time series	Maximum water levels and CSO volumes
Paper	IV and V	VI	VII

## 10.1 Prediction of surcharge, flooding, and combined sewer overflow using reliability techniques and parameterisation of rainfall input.

The purpose of reliability approaches of uncertainty analysis is to find failures. The methods therefore find the set of parameters which have the highest probability of failure. It is presumed that only one set of parameters corresponding to failure exists, i.e. each parameter has a unique value. This is contrary to the GLUE methodology (Beven and Binley 1992), which is based on the concept of equifinality (Beven 2006), allowing different parameter sets to provide the same model prediction (of failure in this case).

In the reliability approaches no conditioning of the model on observation data is conducted, i.e. the parameter uncertainty is propagated directly through the model to an uncertainty estimate of the predictions. However, some comparisons with observations are made (Figure 10.1 and Figure 10.2).

The reliability approaches (especially the First Order Reliability Method) have been extensively applied within the area of structural engineering and building technology (Ditlevsen and Madsen 1996; Madsen et al. 1986; and Melchers 1999), and to some extent within the area of groundwater and river modelling as well as water quality modelling (Portielje et al. 2000; Schaarup-Jensen and Sørensen 1996; Sørensen and Schaarup-Jensen 1995; and Sørensen and Schaarup-Jensen 1996), but as far as the author knows only in the context of urban drainage in this thesis.

### 10.1.1 Methodology

The First Order Reliability Method (Melchers 1999; and Madsen et al. 1986) is an iteration algorithm that searches for failure in a specific system. In this study failure is defined as either occurrence of surcharge or flooding of manholes or whenever the water level in the combined sewer overflow structure exceeds the overflow crest level. The failure function is defined as:

$$g(\mathbf{x}) = H_{crit}(\mathbf{x}) - H_{max}(\mathbf{x}) = 0 \quad (10.1)$$

$H_{max}(\mathbf{x})$  is the maximum water level in either the overflow structure or in a manhole, and  $H_{crit}(\mathbf{x})$  is a critical water level, e.g. the crest level in an overflow structure or the pipe top level or the ground level in a manhole.  $\mathbf{x}$  is a vector of random variables.

The failure function is an *i-dimensional* surface, in which *i* corresponds to the number of included variables. The point on this surface where  $g(\mathbf{x}) = 0$  corresponds to the point with the highest probability of failure - called *the design point*. The First Order Reliability Method works in a standard normal space so that all parameter distributions have to be transformed to this space. The non-linear failure surface is approximated by an *i-dimensional* plane and by iteration. The point in which the plane is a tangent to the design point is found by a finite difference approximation. The failure probability,  $P_f$ , is defined as (Melchers, 1999):

$$P_{f,FORM} = P(g(\mathbf{x}) \leq 0) = \Phi(-\beta) \quad (10.2)$$

$\Phi$  is the standard normal distribution function, and  $\beta$  is the Hasofer & Lind reliability index, which is the minimized distance perpendicular from the linearized failure surface (the point with the highest joint probability density) to the origin in a standard normal space.  $\beta$  represents the point with the largest failure probability, given the probability distributions of  $\mathbf{x}$ .

The point with the highest probability of failure can also be found using different sampling techniques. These have the advantage of not assuming a linear approximation of the non-linear failure surface. In Paper IV and V Monte Carlo Direct Sampling (MCDS) and Monte Carlo Importance Sampling (MCIS) are used to validate the linear approximation of the failure surface using FORM.

### 10.1.2 Inputs and parameters

In order to use the First Order Reliability approach on an urban drainage model, it has been necessary to parameterize the rainfall input, so that synthetic rainfall events are generated based on distributions for some characteristic rainfall parameters. In Paper IV a linear correlation between the rainfall event depth and duration, and the occurrence of overflow is found. Furthermore, a correlation between the rainfall event peak intensity and the maximum water level in manholes is observed. The three characteristic rainfall parameters the rainfall event depth, duration and peak intensity, are fitted to a two-component exponential distribution based on Willems (2000a) and using the recorded time series from the Svenstrup rain gauge (no. 20461). From these distributions synthetic rainfall events are sampled using a truncated Gaussian shaped rainfall event based on Willems (2001). The methodology is presented in Section 7.1.2.

The return period ( $T$ ) of the event corresponding to the design point is easily calculated by:

$$T = \left( P_f \cdot \frac{E}{P_t} \right)^{-1} \quad (10.3)$$

$E$  is the number of events in a given period of time,  $P_t$  (corresponding to the length of the rainfall time series), and the number of failures per time period,  $FPP$  (most often in years) is calculated by:

$$FPP = T^{-1} \quad (10.4)$$

This it is possible to estimate how often either surcharge, flooding, or combined sewer overflow will occur in the drainage system.

Paper IV presents an analysis of the Frejlev catchment, in which only the rainfall input to the MOUSE model is handled stochastically; hydrological and hydrodynamic parameters are not considered. As the algorithm searches for the set of rainfall parameters with the highest probability of failure, this approach can be compared to simple design methodologies with the purpose of determining occurrences of surcharge, flooding, and combined sewer overflow and the associated return periods.

In comparison, Paper IV and V include uncertainties on both hydrological and hydrodynamic parameters. The parameters included in the FORM approach are described in detail in Chapter 8. The rainfall input is assumed to be uniformly distributed over the catchment in every single event. However, the spatial rainfall variation is taken into consideration by applying a wide sampling interval of the hydrological reduction factor, as presented in Section 8.1. A small bias and some dispersion between the Svenstrup rain gauge (no. 20461) and the gauges located in the Frejlev catchment (no. 20456 and 20458) are observed in Appendix A. The bias and dispersion are included as a source of rainfall uncertainty in the analysis.

In Paper V, the simulations are only implemented for occurrence of combined sewer overflow and not for surcharge and flooding.

### 10.1.3 Results

Figure 10.1 presents the frequencies of combined sewer overflow using FORM and the two Monte Carlo approaches (MCDS and MCIS). The results of a deterministic long term simulation (LTS, Paper II and III), using mean parameter values, and the long term Monte Carlo simulations (LTSMC, Paper VII) are also shown. Furthermore, the mean number of overflow occurrences in the period 2004 – 2006 is presented, using the observation data from the Municipality of Aalborg. It is evident that the reliability approaches (FORM, MCIS, or MCDS) show similar results, indicating that the linear approximation of the failure surface in FORM is valid. The simulations, in which only the rainfall input is parameterized show a

lower frequency of overflow occurrence compared to the simulations in which the parameter uncertainty is included and the latter fits quite well to the observations. However, it is important to emphasize that these are only based on three years of data (2004-2006) and the simulations are based on approx. 20 years (1979-1990 and 1998-2005). Furthermore potential climate changes might also affect the results. The overflow predictions using the long term Monte Carlo (LTSMC) approach have a somewhat smaller mean frequency, but the 95 % confidence interval brackets the observations well. Comparing the LTS simulation with the LTSMC simulations, it is shown that the former has a lower mean value of frequency than the latter. If all the parameters in the LTSMC approach were sampled from a normal distribution, the predicted means from the two approaches would be equal, but this is not the case.

Figure 10.2 presents the frequencies of flooding of the most critical manhole in the Frejlev catchment. This manhole is not representative for the whole catchment and is merely chosen to illustrate the methodology. FORM, MCIS and MCDS show similar results, again indicating that the linear approximation using FORM is valid. These predictions are not implemented with the whole range of parameters, but this is clearly something to investigate further. As the predicted overflow frequencies show quite a difference between the reliability approaches with and without parameter uncertainty, these flooding occurrences are not commented any further, as it would be pointless to compare with LTS and LTSMC.

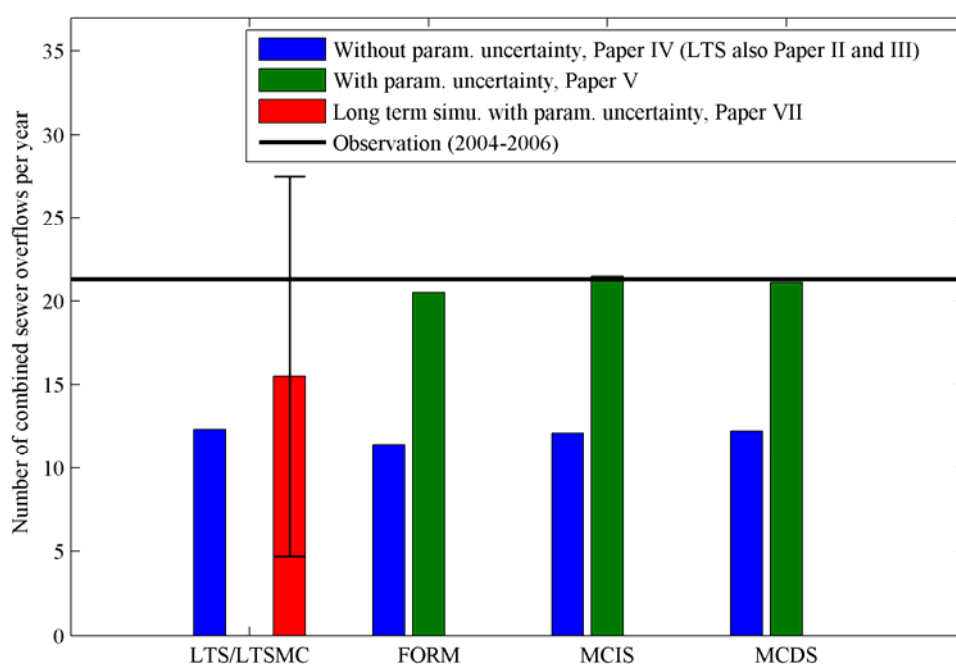


Figure 10.1 Comparison between results from Paper IV, V and VII regarding simulation of combined sewer overflow. The vertical line on the red bar marks the 95 % confidence interval.



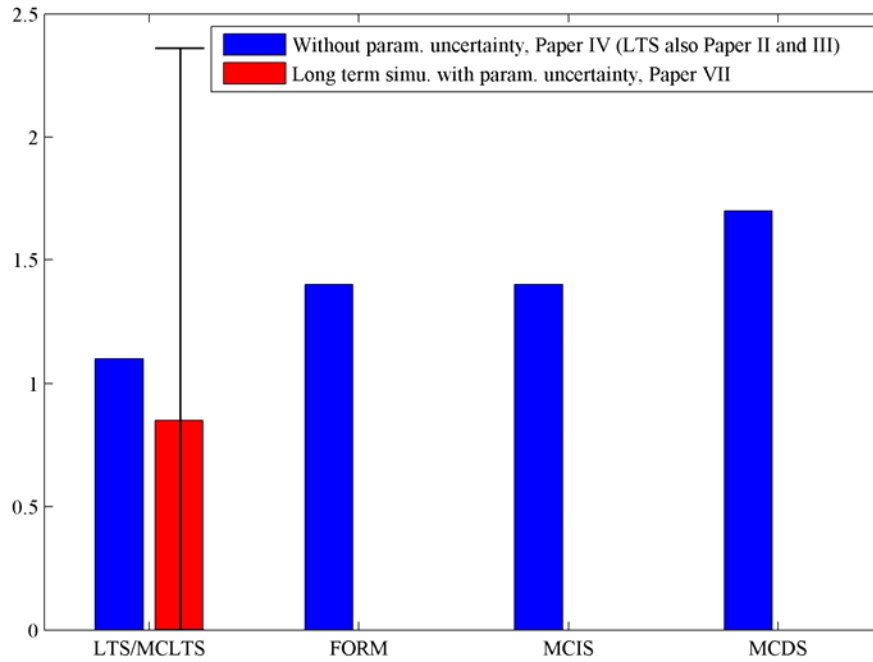


Figure 10.2 Comparison between results from Paper IV and VII regarding flooding simulation in the most critical manhole in the Frejlev catchment (no. T013520). The vertical line on the red bar marks the 95 % confidence interval.

#### 10.1.4 Discussion

The proposed methodology for parameterisation of the rainfall input in order to generate synthetic rainfall events has proven very useful to predict occurrences of combined sewer overflow or surcharge/flooding. The methodology can be considered an alternative to other approaches applying a synthetic event based rainfall input e.g. the Chicago Design Storm, CDS (Kiefer and Chu 1957). The advantage of the proposed methodology is, however, the possibility for performing prediction of combined sewer overflow occurrences, which is not possible doing CDS simulations. The approach presented in Paper IV, without randomization of parameter uncertainties, can be applied as presented, with mean parameters corresponding to a traditional CDS model. The real benefit of the model is, however, the possibility to include parameter uncertainty as well (Paper V).

Obviously, some errors are introduced by simplifying the rainfall input when applying synthetic events. In the papers it is, however, shown that these simplifications do not affect the predicted extremes, i.e. surcharge, flooding, or overflow. With regards to the first, it is shown that the vast majority of these only depend on the peak intensity averaged over a period of time corresponding to the transportation time in the system. Likewise the overflow prediction only depends on the rainfall event depth and duration, as a large storage is filled before occurrence of overflow. This smoothens out the inflow hydrograph to the overflow structure and minor fluctuations are neglected.

The good fits between the characteristic rainfall parameters and the predictions are evidently dependent on the system in question. The predictions in the Frejlev catchment performs quite linearly, which has been a benefit when applying the proposed methodology. One could imagine a larger drainage system with more branches, potential backwater effects, more pumps, etc. which might fail down stream in the system due to non-linearity between the input and the response.

Compared to traditional long term simulation, using observed rainfall time series input, the methodology has an advantage due to the fact that simulations can be executed much faster. In the Frejlev catchment the simulation time, using FORM is approx. 2 hours, compared to the LTS simulation of 12 hours, and the LTSMC simulations of approx. 12,000 hours. A disadvantage compared to the two LTS approaches is, nevertheless, that it is only possible to predict occurrences of overflow/surcharge/flooding and not, for example, overflow or flooding volumes.

Another drawback is that for each point in the drainage system which is to be investigated (either a manhole or an overflow structure) a new optimisation simulation has to be carried out. This is due to the fact that the optimal characteristic rainfall parameter values are closely connected to the location in the system. Some automated loop approach including all manholes, or at least the most important, could probably be implemented, but is not considered in the present.

In the study the three optimisation methodologies (FORM, MCIS, MCDS) are investigated. However, several other reliability methodologies could have been applied. For example the Second Order Reliability Method (SORM), which includes a second order approximation of the failure surface (Madsen et al. 1986; and Melchers 1999).

## 10.2 Event based stochastic time series calibration

This approach presents an application of the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley 1992). It is a methodology of uncertainty estimation in which historical observation data is taken into account, and is therefore considered a stochastic method of calibration. The investigation is presented in detail in Paper VI. Compared to the other probabilistic applications presented in this thesis, this is the only one in which an actual reduction of prediction uncertainty is considered.

Several authors have applied the GLUE methodology, e.g. in integrated and urban water quality modelling (Freni et al. 2007; Lindblom et al. 2007; and Mannina et al. 2006); in hydrological modelling of rivers and groundwaters (Beven and Freer 2001; Freer et al. 1996; Jensen et al. 2004; and Jensen 2002); and in hydraulic modelling (Aronica et al. 1998; Hankin et al. 2001; Pappenberger et al. 2005, 2007; Romanowicz et al. 1996; and Romanowicz and Beven 2003). The methodology has, as far as the author knows, only been applied in hydraulic urban drainage modelling in Aronica et al. (2005).

The purpose of the investigation is to perform a stochastic calibration, in which the Frejlev setup of the MOUSE model is conditioned on flow measurements and overflow registrations. Moreover, it is investigated whether either the Time-Area or the Kinematic Wave surface runoff model, predicts the observed flow time series more accurately than the other. Furthermore, it is investigated if predictions are improved using an average of two local rain series as input compared to applying only one.

### 10.2.1 Methodology

The concept of the GLUE methodology is to execute a large number of Monte Carlo simulations with random parameter sets selected from prior probability density functions for each parameter. For each model simulation a likelihood measure is calculated in order to reflect the goodness of fit in comparison with an observation dataset. Simulations that are not considered to be acceptable are rejected as non-behavioural. From the remaining set of behavioural simulations, it is possible to derive posterior probability density functions for both parameters and predictions using the likelihood measure as a weighting factor. The intention is to allow for the demonstrated possibility that many different models and parameter sets might provide acceptable predictions when compared with the available observations. (Beven and Binley 1992; and Beven 2001, 2006, 2008).

Using traditional Bayesian approaches of uncertainty analysis is based on formal definitions of likelihoods. However, in the GLUE methodology the likelihood measure is defined empirically. In modelling of discharge time series, Beven and Freer (2001), and Freer et al. (1996) have shown that the following definition is suitable:

$$L_j(\mathbf{O}_j | \mathbf{M}_j(\boldsymbol{\Theta}, \mathbf{I})) \propto \exp\left(\frac{-\sigma_{\mathbf{M}_j - \mathbf{O}_j}^2}{\sigma_{\mathbf{O}_j}^2}\right) \quad (10.5)$$

$\mathbf{L}$  is the empirical likelihood;  $\mathbf{O}$  is the observations conditional on the model ( $\mathbf{M}$ );  $\boldsymbol{\Theta}$  is a set of parameters;  $\mathbf{I}$  is the input;  $\sigma_{\mathbf{M}_j - \mathbf{O}_j}^2$  is the variance of the residuals between model and observations; and  $\sigma_{\mathbf{O}_j}^2$  is the variance of the observations. This definition is especially suitable in fitting the peaks, which are considered the most important derived output from the time series considering surcharge and flooding. Moreover, it ensures low volume errors. These are especially important in prediction of combined sewer overflow. A perfect fit between model and observation equals a likelihood of 1, if the error between model and observations is large the likelihood approximates 0.

The MOUSE model setup is the one presented earlier in the thesis. However, the output from the model is the flow time series in the pipe sections, in which the two flow meters are located. Furthermore, a time series of the overflow discharge is extracted. Thus, it is possible to condition the model on the observed flow time series as well as the binary registration of overflow occurrence.

The likelihoods in the overflow structure are defined by the overflow duration ( $dur$ ):

$$L_{III}(\mathbf{O}_{III}|\mathbf{M}_{III}(\boldsymbol{\Theta}, \mathbf{I})) \propto 1 - \frac{|dur_M - dur_O|}{dur_O} \quad (10.6)$$

A combined likelihood measure is defined using different weights ( $w$ ) between the three observation points:

$$L(\mathbf{O}|\mathbf{M}(\boldsymbol{\Theta}, \mathbf{I})) \propto w_I L_I \cdot w_{II} L_{II} \cdot w_{III} L_{III} \quad (10.7)$$

The posterior distributions (the likelihood of the model conditional on the observations) are calculated by weighting the prior ( $L_o(\mathbf{M})$ ) using the likelihood of the observations conditional on the model:

$$L(\mathbf{M}(\boldsymbol{\Theta}, \mathbf{I})|\mathbf{O}) = L_o(\mathbf{M}) \cdot L(\mathbf{O}|\mathbf{M}(\boldsymbol{\Theta}, \mathbf{I})) / C \quad (10.8)$$

$C$  is a scaling constant.

### 10.2.2 Inputs, parameters, and observation data

The three different conceptual setups of the MOUSE model are implemented as:

- A1:* A Time-Area surface runoff model with one rain series (gauge no. 20456) as model input.
- A2:* A Time-Area surface runoff model with area weighted rain series (gauge no. 20458 and 20456) as model input.
- B2:* A Kinematic wave surface runoff model with area weighted rain series (gauge no. 20458 and 20456) as model input.

In order to do the analysis based on the best possible dataset, the periods in which data from all observation points (the two rain gauges in Frejlev, no. 20456 and 20458, as well as flow measurements and overflow registrations) overlaps are found. Applying a criterion of a minimum rain depth of 5 mm leads to 6 independent rainfall/runoff events from 2004 which are used for calibration and 3 events from 2006 which are used for validation.

The prior parameter distribution is presented in Table 1, Paper VI. These are implemented as either a normal or a uniform distribution, both with wide sampling intervals.

### 10.2.3 Results

The calibration events are simulated by 10,000 runs for each setup. The computation time of one set of six simulations is approx. 20 minutes. This leads to a total computation time of 10,000 hours for the calibration events. The validation events are only implemented using the “best” of the conceptual setups, and therefore the computation time is approx. 1700 hours, doing the same number of simulations. Fortunately, it has been possible to use a cluster of computers to do the simulations. One of the calibration setups is implemented using 20,000 simulations in order to check if an appropriate number of Monte Carlo runs are implemented. Results show no remarkable difference between 5,000, 10,000 and 20,000 simulations, and it is concluded that 10,000 simulations are definitely enough.

The separation between behavioural and non-behavioural model simulations is carried out on the basis of a likelihood of  $L > 0.3$ , which is considered a reasonable criterion of acceptability; cf. the *Discussion of acceptability criteria and weighting of likelihoods* in Paper VI.

Figure 10.3 presents a so-called dotted plot for *setup B2*, in which the calculated likelihoods are shown as a function of the sampled parameter values. The sub plots with no significant peak are either (1) a clear indication of equifinality, i.e. that it is possible to have the same maximum likelihood regardless of the parameter value; or (2) an indication of very little sensitivity with regards to model predictions. Figure 10.4 shows sensitivity plots in which cumulative distribution functions (cdf's) of behavioural simulations and non-behavioural simulations are plotted. If the cdf's are identical, the sensitivity of the parameter in question is low (Beven 2008; Hornberger and Spear 1981).

The hydrological reduction factor shows a quite narrow peak in Figure 10.3, which corresponds to the mean value of the parameter as presented in Chapter 8, Paper I, and Appendix C. Moreover, it is obvious that the hydrological reduction factor is by far the most sensitive parameter (Figure 10.4). Other parameters show very little sensitivity towards model predictions. The dotted and sensitivity plots of the other conceptual setups show similar results.

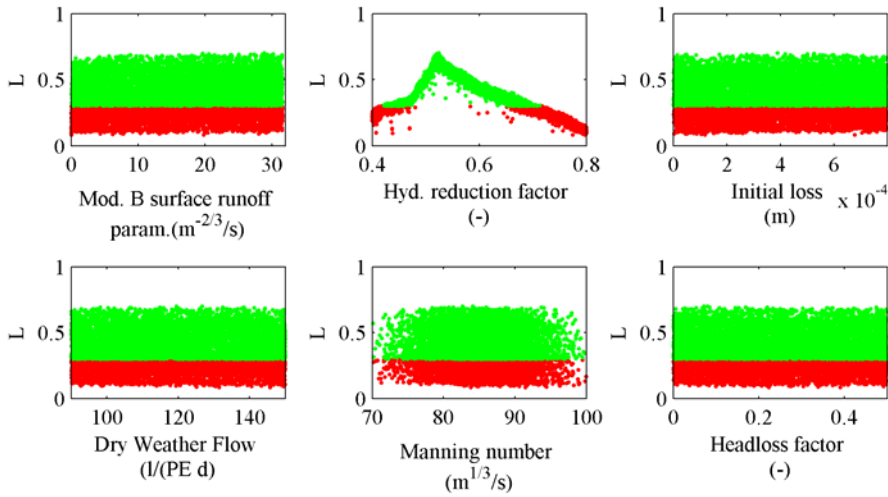


Figure 10.3 Combined likelihoods over all calibration events as a function of parameter values for the conceptual setup B2. Accepted simulations with  $L > 0.3$  are shown in green.

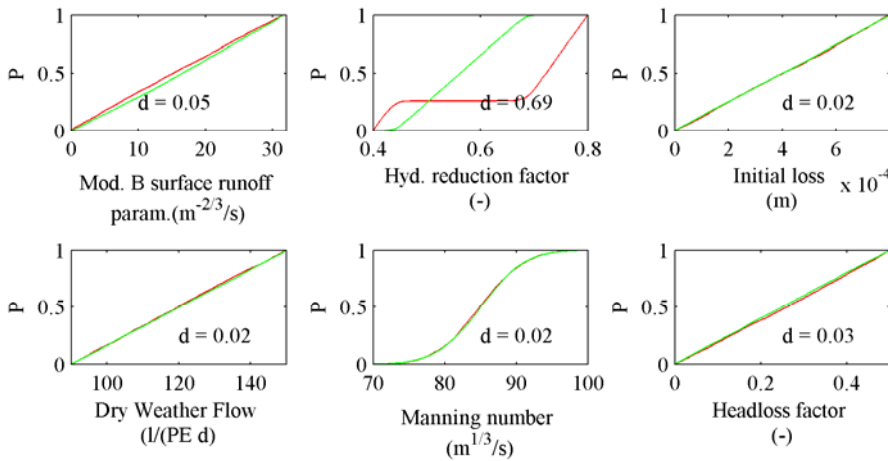


Figure 10.4 Cumulative distribution functions of behavioural (green) and non-behavioural (red) simulations, setup B2.

Figure 10.5 illustrates an example of predicted and observed time series in one of the simulated events. The observations are not completely bracketed by the confidence intervals, and evidently a complete bracketing is the purpose of the GLUE methodology. More time series plots are shown in the paper. In Table 10.2 the percentage of the time (for all calibration events) in which the observations are bracketed by the prediction intervals is presented.

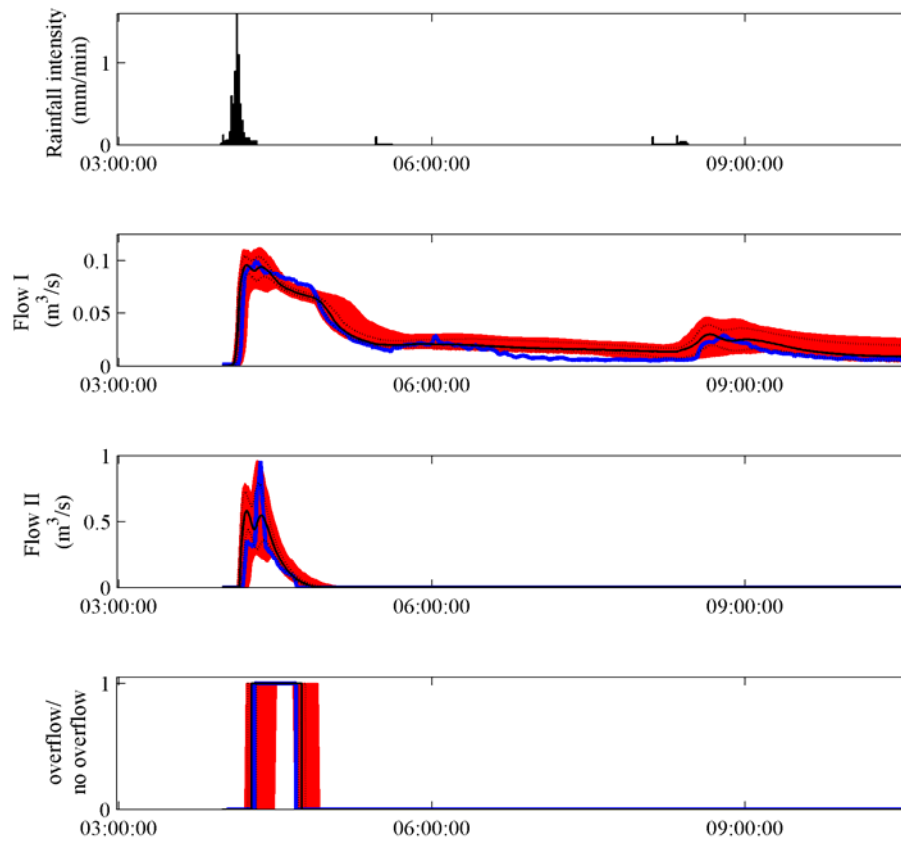


Figure 10.5 Calibration event no. 4 with conceptual setup B2. The bold blue line is the observed time series, the red area covers the whole prediction interval, and the black lines indicate the 2.5 %, 50 %, and 97.5 % prediction intervals.

Table 10.2 Results of the three conceptual setups

Conceptual setup	Accepted simulations out of 10000	$L_{\max}$	Percentage of time in which model predictions brackets the observations, flow meter I (%)	Percentage of time in which model predictions brackets the observations, flow meter II (%)
A1	3838	0.704	29	57
A2	4390	0.720	35	58
B2	6091	0.700	36	58

In the simulation of the validation events the prior distribution of the hydrological reduction factor is narrowed corresponding to the posterior distribution. The other parameters show very little sensitivity, and are left unchanged. The optimum of the hydrological reduction factor, with regards to the validation events, however, is outside of the posterior distribution. Therefore, the validation is carried out using the same priors as in the calibration. Thus, the validation is considered a second calibration. This clearly indicates that the hydrological reduction factor is the most dominant parameter. The fact that it is used to account for some of the uncertainty of the rainfall input makes it vary a lot from event to event. If for example a rain storm has just covered the rain gauge and not the rest of the Frejlev catchment, a smaller observed runoff than if the rain was distributed over the whole catchment would be observed. In order to adjust the predicted runoff volume to the observed runoff volume, the reduction factor would adopt a high value. For the same reason some event specific reduction factors might be larger than 1.

#### 10.2.4 Discussion

It is evident by comparing the number of accepted simulations in Table 10.2 and the percentage of time in which the observed time series is bracketed by the prediction interval, that the *B2* setup predicts the observed time series the best. It is therefore concluded that an area weighted mean of time series from two rain gauges predicts the flow time series more accurately than when using only one rain gauge. It would be interesting to see if the predictions are further improved if the two rain gauges are implemented so that they each represent a part of the catchment, i.e. a semi-distributed rainfall input. This is, however, not considered in the thesis. Furthermore, it would be interesting to investigate whether the inputs from the Svenstrup rain gauge (no. 20461) might predict as accurately as when applying the local rain gauges. Especially as the Svenstrup gauge is used to make long term predictions, Section 10.3 and Paper VII.

The reason why *setup B2*, predicts the hydrographs better than *setup A2*, is due to the application of the Kinematic Wave surface submodel. As shown on Figure 5.4, the Kinematic Wave approach has large tails compared to the Time-Area model. Therefore the large tails from each sub-catchment propagate through the model so that tails are larger at the observation points. Comparing Figure 10.6 with a similar figure with *setup A2* (not shown) it is obvious that *setup A2* underestimates the hydrograph tails.

The peak flow values and the runoff volumes are predicted somewhat identically in the three setups. To exemplify this, CDF's of the predicted mean (of the six events) peak flow values as well as mean runoff volumes are given in Figure 10.6 (for both observation points). Furthermore, the predicted mean overflow duration is shown. It is evident that regardless of the conceptual model setup, no remarkable difference between the peak flows, runoff volumes and overflow durations are present. Comparing the predicted maximum water levels at different locations in the drainage system, the tendency is the same. Thus, it is concluded that the setups perform equally well in prediction of maximum water levels and combined sewer overflow volumes. This conclusion is applied as an assumption in Paper VII.

Despite similar results on predicted peak values, volumes and durations, the observed hydrographs are not in any of the nine simulated events bracketed 100 % percent of the time by the prediction interval. The reason is probably poor prediction of the tails. Even though *setup B2* shows the best tail prediction, it still does not fit completely within the confidence bands. Another reason might be an insufficient rainfall input. This may be improved using a spatially distributed input, e.g. using weather radar data. Other reasons for the incomplete fits may also be that all parameters are considered global, i.e. the same values are applied everywhere in the catchment and sewer system. A fully or semi-distributed model with local parameters might be considered. This would, however, increase the number of parameters and therefore also the number of required simulations significantly. Further applications with a more distributed rainfall input, more calibration events, and possibly more distributed parameters might be interesting to investigate in another paper, as the GLUE methodology has proven very applicable in urban drainage modelling.



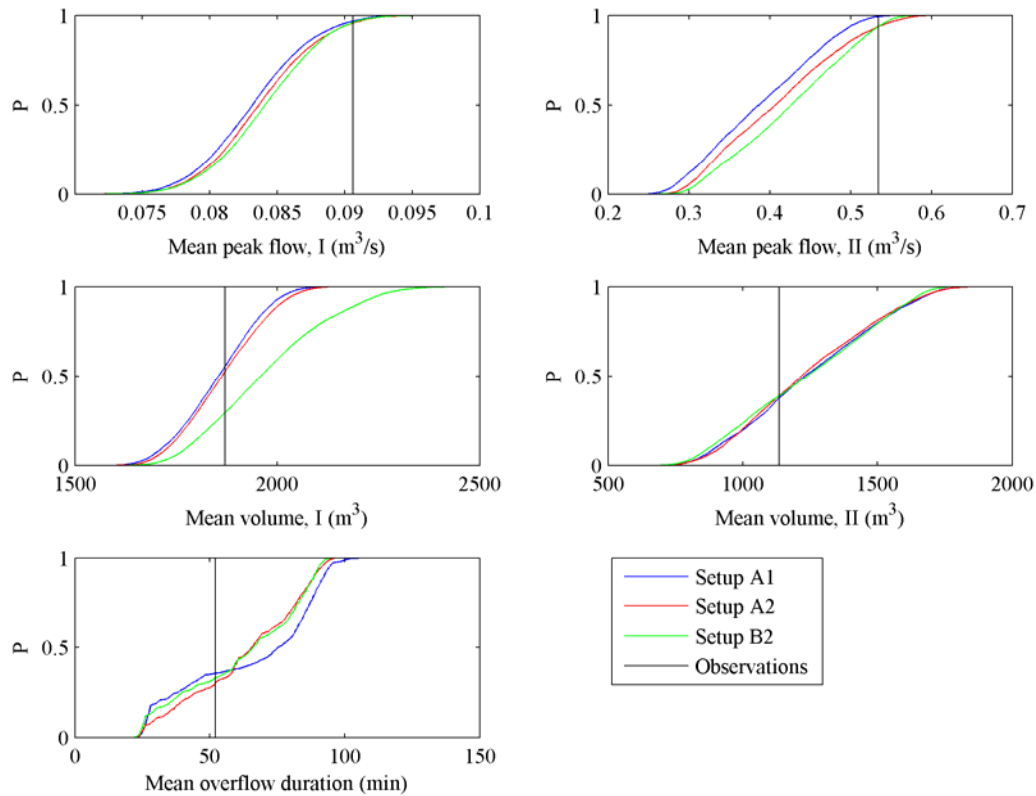


Figure 10.6 Cumulative distribution functions of prediction means of the 6 events.

### 10.3 Long term stochastic prediction of maximum water levels and combined sewer overflow volumes

Based on the results from the GLUE analysis, this section presents a forward uncertainty analysis (Beven 2008), in which the primary purpose is to investigate extreme statistics and the uncertainties related to these. It would be preferable to do this analysis by conditioning on historical data as well. Doing long term simulations, however, would require many years of observations in order to get the predicted return periods correct. A conditioning on all available flow data from the ten years of registration in Frejlev will probably be the content of another paper, but is not considered in the thesis.

The uncertainties of extreme events statistics involve, besides the uncertainty on maximum water levels and overflow volumes, the uncertainty associated with the assessment of return periods. Traditionally, return periods are assessed by a ranking of e.g. the maximum water levels for each event in a specific manhole, so that the largest event is assigned to the simulation period. This involves considerable uncertainty on the large return periods as these are assessed by the simulated period of time, and not the real occurrence. Therefore, this section and Paper VII, presents a new methodology for assessing the return periods more accurately, by use of correlations between characteristic rainfall parameters and model predictions as well as many years of rainfall statistics.

### 10.3.1 Methodology

The long term simulations are carried out doing direct Monte Carlo sampling based on the parameters and input described in the next section. Even though it was found the in GLUE analysis that the Kinematic Wave surface submodel predicts the flow time series the better than the Time Area submodel, it is chosen to apply the Time-Area surface submodel in this approach, as no remarkable difference is shown examining the maximum water levels and the runoff volumes.

The return periods of maximum water levels and combined sewer overflow volumes are estimated both by ranking and by a new proposed methodology presented in Paper VII. A correlation between characteristic rainfall parameters (event peak intensities, depths, and durations) and predictions of water levels and combined sewer overflow is presented. The return periods of these characteristic rainfall parameters can be assessed quite accurately using a Generalised Pareto model fitted to data from several Danish rain gauges (Madsen and Rosbjerg 1997a, 1997b; Mikkelsen et al. 1998; Madsen and Arnbjerg-Nielsen 2006; Spildevandskomiteen 2006). Therefore, the idea of the proposed methodology is to estimate the return periods of maximum water levels and combined sewer overflow volumes using the correlation between the characteristic rainfall parameters and the water levels and volumes.

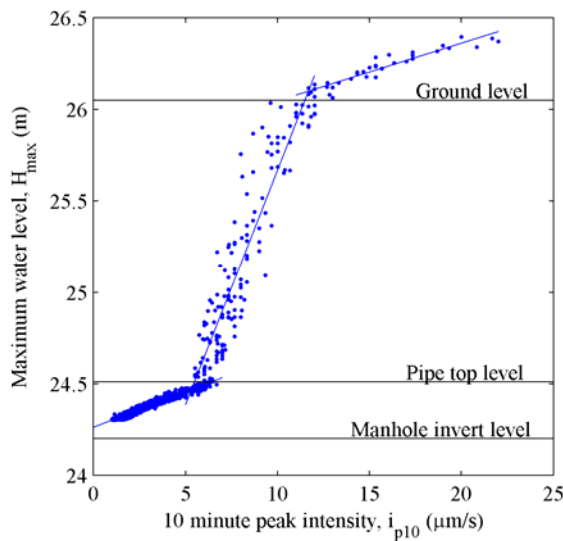


Figure 10.7 Relationship between the maximum event water level and the 10 minute peak intensity in Manhole T013520.

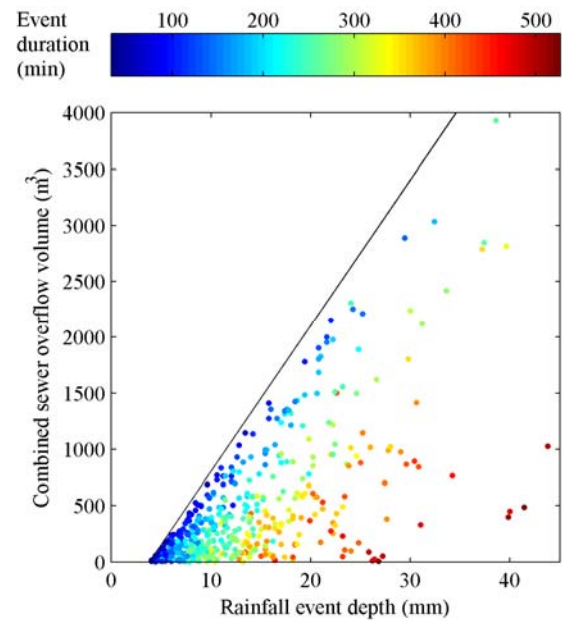


Figure 10.8 Relationship between the rainfall event depth and the overflow volume. The colour graduation indicates the rainfall event duration.

Figure 10.7 presents the relationship between the event peak intensity averaged over 10 minutes ( $i_{p10}$ ) and the predicted maximum water level ( $H_{max}$ ) in a manhole. This plot is made by a deterministic simulation with a combined long rain series from Odense, Denmark. The rain series is not representative for the Frejlev catchment and is selected only due to its length of 58 years. As the peak intensity and the maximum water level shows a good linear correlation ( $i_{p10}$ - $H_{max}$ -correlation), it is possible to estimate the return period of the maximum water level applying the return period of the rainfall intensity. In each simulation of the water level, the mean values and confidence limits of the Pareto return period model corresponding to the event peak intensity are read (Figure 7.7). The return period is then sampled 100 times applying a triangular distribution.

Likewise, Figure 10.8 shows the correlation between combined sewer overflow volumes and event depths and durations ( $d$ - $dur$ - $V_{CSO}$ -correlation). The diagonal line corresponds to the maximum runoff volume as a function of the rainfall depth, i.e. the impervious area multiplied by the hydrological reduction factor and the rainfall depth. A linear correlation between the event duration and the minimum rainfall depth which will generate overflow is also present. Therefore, the overflow volume can be estimated by the rainfall event depth and duration as well as the impervious area and the simulation specific hydrological reduction factor. The return period of the CSO volume is therefore estimated based on the return period of the rainfall event depth. Likewise, the water levels, the mean values and confidence limits of the Pareto return period model corresponding to the event depth are read (figure 7.8), and the return period is then sampled 100 times applying the triangular distribution.

### 10.3.2 Inputs and parameters

The long term simulations are carried out applying the Svenstrup rain series, as this is the longest of the available local rain series (approx. 20 years and 780 events with a rain depth larger than 1 mm). The parameter inputs are the posteriors from the GLUE analysis, Section 10.2 and Paper VI. The hydrological reduction factor is sampled from a normal distribution, with a slightly larger standard deviation than the posteriors. It is hereby possible to generate values, representing all the observed events (see e.g. Figure 8.1) and not just the six events applied in the GLUE analysis.

### 10.3.3 Results

The long term Monte Carlo simulations are simulated by 1,000 runs of the 780 events. The simulation time of one long term simulation is approx. 12 hours, i.e. the total computation is approx. 12,000 hours. In order to investigate whether 1000 simulations are adequate, a comparison on maximum water levels and CSO volumes applying 500 and 1,000 simulations are conducted. No significant difference is observed, and it is concluded that 1,000 simulations are adequate.

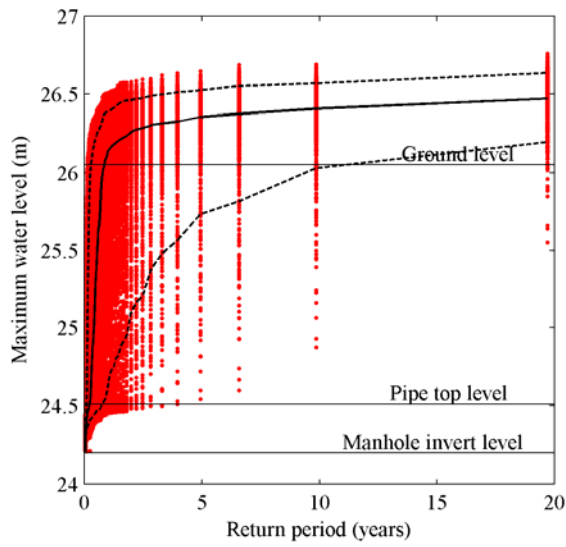


Figure 10.9 Return periods by ranking of maximum water levels, Manhole T013520. The solid line is the median and the dotted are the 95% confidence interval.

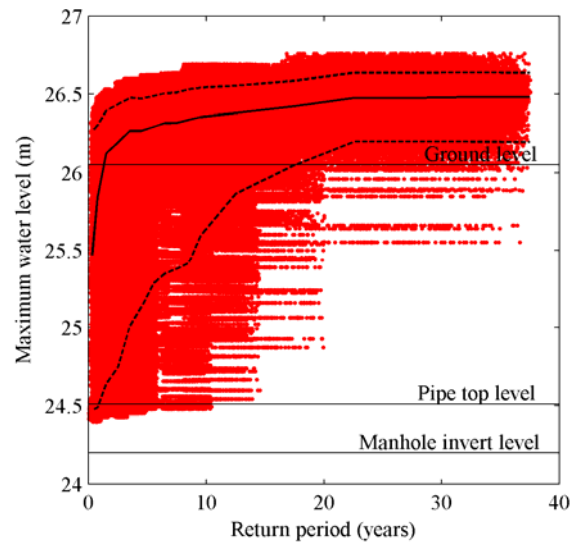


Figure 10.10 Return periods by intensity-water level correlation, Manhole T013520. The solid line is the median and the dotted are the 95% confidence interval.

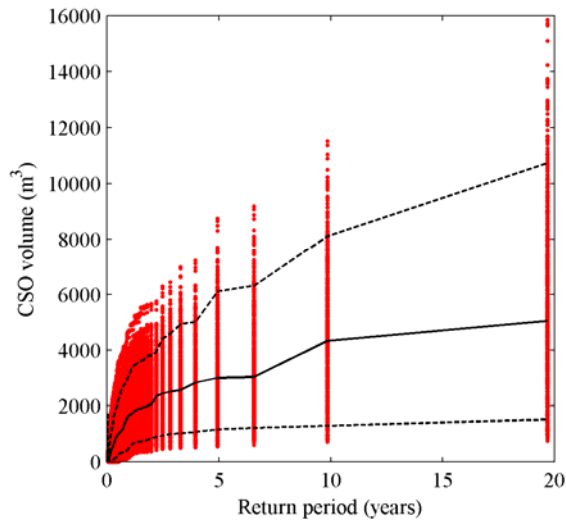


Figure 10.11 CSO volumes and return periods by ranking. The solid line is the median and the dotted are the 95% confidence interval.

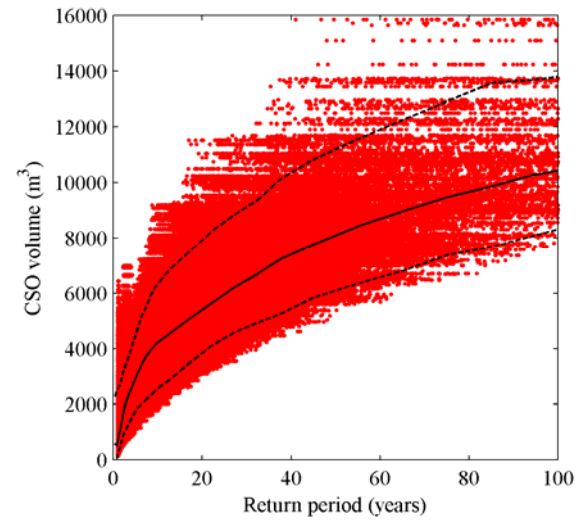


Figure 10.12 CSO volumes and return periods by  $i_p$ - $H_{max}$ -correlation. The solid line is the median and the dotted are the 95% confidence interval.

The traditional ranking methodology to estimate return periods of water levels is presented in Figure 10.9 for the most critical manhole in the system (Manhole T013520, Figure 3.2). It is evident, doing the 1000 Monte Carlo simulations, that the dispersion in the predicted water levels for this manhole is significant. This is primarily due to the standard deviation applied on the hydrological reduction factor, as this is by far the most crucial parameter. Figure 10.10 presents the maximum water levels and return periods estimated by the  $i_p-H_{max}$ -correlation and the Pareto model. Comparing the two figures, it is clear that the return periods are similar at low values. However, the return period predictions of Figure 10.9 are more uncertain on the high values, as the maximum return period is applied equal to the time series length. As the  $i_p-H_{max}$ -correlation, using the Pareto model, has no upper limit, the predicted water levels are assigned a larger return period.

The prediction of CSO volumes using the ranking methodology is presented in Figure 10.11. Again, the confidence interval on the predicted volumes is quite wide, and the uncertainty on the large return periods are large compared to the approach in which the  $d\text{-dur-}V_{CSO}$ -correlation is applied, Figure 10.12. Figure 10.13 presents the two confidence bands from Figure 10.11 and 10.12. It is evident that the confidence interval is narrowed when applying the proposed method. This is due to an estimation of larger return periods to the CSO volumes.

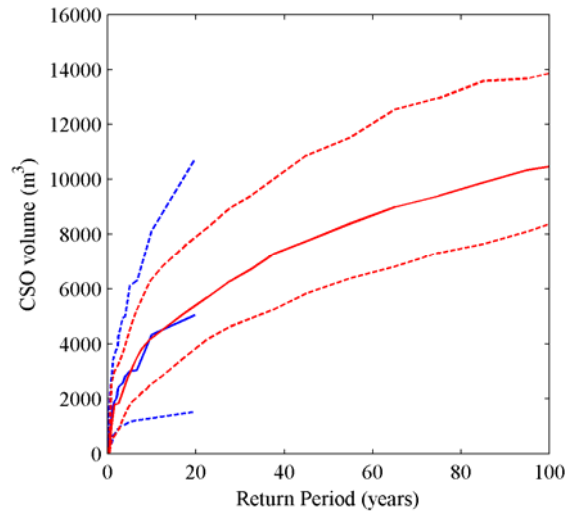


Figure 10.13 Comparison of confidence intervals of CSO volumes applying the ranking methodology (blue) and the proposed methodology (red)

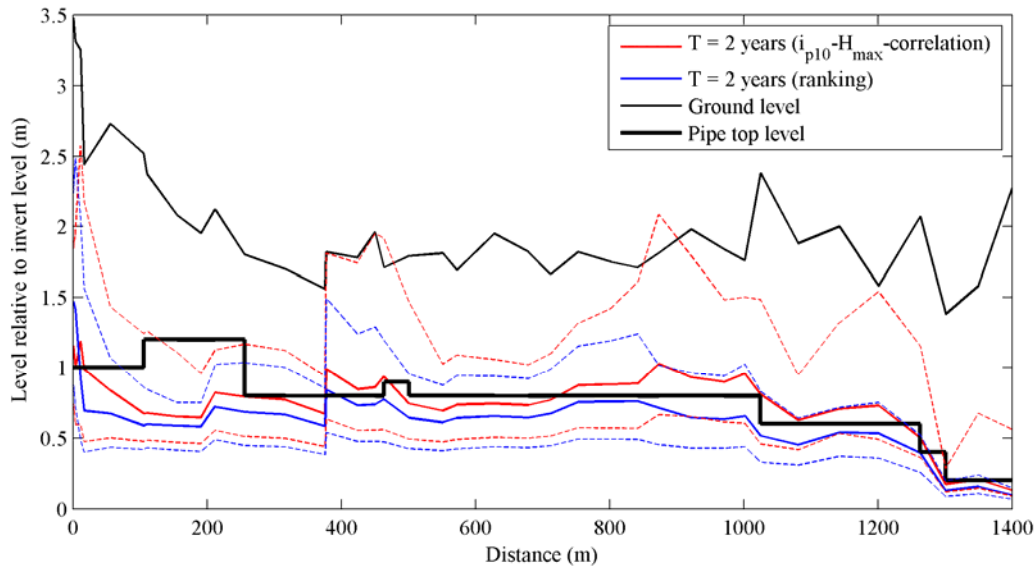


Figure 10.14 Profile plot of median maximum water levels (solid) and confidence bands (dotted) for return periods of 2 years applying the two methodologies to estimate return periods. The profile corresponds to the main pipe line (thick red line on Figure 3.2).

#### 10.3.4 Discussion

The predicted maximum water levels and CSO volumes have quite large confidence bands. This is primarily due to the large sampling interval of the hydrological reduction factor. The confidence bands may be narrowed, if conditioning on observations was implemented e.g. applying GLUE.

The Long term Monte Carlo simulations in which the return periods are assessed by ranking are uncertain on the large return periods, as these are assessed corresponding to the length of the rain series. Willems (2000b) has suggested that a maximum of 10 % of a rain series period gives statistically reliable results. Applying this definition, a reliable prediction can be given up to and including 2 years in this study. Compared to the results in which the return periods are estimated by the derived correlations, it is evident that the results are similar on the return periods below 2 years (Figure 10.13). Figure 10.14 presents a profile plot of the main sewer line, in which the 2 year return periods of maximum water level for the two approaches are plotted. Some minor deviations are present on the medians and the confidence intervals. The 2 year return period corresponds to the design criteria for surcharge (if the pipe top level is exceeded) for new drainage systems. A plot showing the 10 year return period (corresponding to the design criteria for flooding - if ground level is exceeded) would be preferable, but very few occurrences of the 10 year return period were predicted using the  $i_{p10}$ - $H_{max}$ -correlation and Pareto model.

The proposed methodology to estimate return periods is shown to be very applicable, even though some more validation of the approach still needs to be done. The derived correlations require a drainage system which performs linearly (as was also the case with the FORM approach) and therefore it can not be stated if the approach will work on larger and more branched drainage systems.

The long term Monte Carlo simulations are not applicable for non-research purposes as the computation time is very long. However, the results clearly show that doing deterministic prediction of maximum water levels and CSO volumes may be quite random depending on the chosen parameter values.

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# Chapter 11

## Conclusion and Recommendations

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*This chapter presents the main conclusions of the thesis as well as suggestions for further investigations and general recommendations for other modellers of urban drainage systems.*

### 11.1 Conclusion

The use of urban drainage models for analysis of drainage systems has evolved extensively during the past decades, but due to natural variability, lack of knowledge, and empirical assumptions, the uncertainties within these models are still significant. In the design of new systems or analyses of existing drainage systems, this may lead to over-dimensioned drainage systems, with excessive construction costs and potentially poor self cleaning. On the other hand, if the necessary safety is not implemented in the methods, under-dimensioned drainage systems may be a result, and too frequent flooding or too frequent combined sewer overflow to receiving waters might occur.

The object of the thesis has been, based on the above, to locate and evaluate the uncertainties related to methods, inputs, and model parameters in urban storm water drainage models in order to investigate in what way the uncertainties affect the model predictions, especially the extreme event statistics (i.e. maximum water levels in manholes and combined sewer overflow volumes). The thesis includes a few deterministic approaches in which different modelling and parameter aspects are investigated. Furthermore, stochastic procedures for implementation of the input and parameter uncertainties are presented in order to generate a prediction uncertainty estimate. Three very different methodologies of uncertainty propagation are investigated in the thesis. These are chosen with regard to their applicability within other areas of research, and a confidence that they might work well to implement the uncertainties in the context of urban drainage modelling.

The first of the three methodologies is based on a parameterisation of the rainfall input, so that it is possible to generate Gauss shaped synthetic rainfall events. Introducing probability distributions for different parameters and inputs, the methodology aims at finding the set of parameters, which has the largest probability of failure. In this case, failure is defined as either occurrence of surcharge, flooding, or combined sewer overflow. Three different reliability approaches are applied; the First Order Reliability method, Monte Carlo Importance



Sampling, and Monte Carlo Direct sampling. Similar results are obtained applying the three methods. The parameterisation relies on linearity between the rainfall peak event intensity and the predicted maximum water levels in manholes as well as linearity between the rainfall event depth and duration and the overflow volumes. In order for these relationships to be linear, the drainage systems have to be quite simple, and the methodology might not work on more complex systems. The application of Gauss shaped synthetic rainfall events, is shown to be applicable to predict both surcharge, flooding, and combined sewer overflow and presents a strong alternative to simple design or analysis methodologies.

The second of the three stochastic approaches is the only one with purpose of reducing the uncertainty. The Generalized Likelihood Uncertainty Estimation (GLUE) methodology is applied in order to carry out a stochastic calibration based on observed flow time series and overflow registrations. Different conceptual setups, with different surface runoff models, are tested and different rainfall input is tested in order to predict the observed flow time series most accurately. These are described in the following sections. The methodology has shown to be very applicable in the context of urban drainage modelling, as it is possible to predict time series somewhat equally to observations time series and furthermore, to derive posterior parameter distributions.

The final stochastic approach is based on results from the stochastic calibration. Doing long term simulations on approx. 20 years of historical rainfall data, it is possible to predict confidence bands of both maximum water levels in manholes as well as combined sewer overflow volumes. Furthermore, in order to handle the uncertainty with regards to the return periods, a new methodology is proposed, applying correlation analyses between input and response in the drainage model and statistics from several Danish rain series. This approach is compared with a traditional ranking approach to estimate return periods. The methods show similar results on the low return periods, but on the large return periods the proposed methodology is expected to be more reliable. This, however, can not be verified as no historical water level or overflow data is available. The new method predicts larger return periods than the length of the rain series and therefore the confidence bands on the large return periods are reduced compared to the ranking method.

Prior to the completion of the presented stochastic approaches, a division of uncertainties related to urban drainage models is proposed introducing a pentad. The elements in the pentad are *model methodological uncertainties*, *physical structure uncertainties*, *input data uncertainties*, *calculation parameter uncertainties*, and *observation data uncertainties*. Each of the elements are presented in the following:

The model methodological uncertainty is shown to be a minor source of uncertainty compared to the input data and calculation parameter uncertainties. The applications used throughout the study are quite complex and it is expected, if simpler and possibly more lumped parameter models are applied, that the uncertainty might increase. Despite the rather small contribution to the overall uncertainty, it has been possible to distinguish between two surface runoff sub-models, the Time-Area model and the Kinematic Wave model. The latter is shown to contain less model uncertainty, as a better prediction of tem-

poral flow variation is present. However, in prediction of extremes (maximum water levels and combined sewer overflow volumes), the two sub-models perform equally. Better local observation data might help improve the sub-models, so that a calibration of only one sub-catchment might be implemented.

For the hydrological part of the surface sub-model, it is decided to apply a simple linear relationship (using the impervious area and the hydrological reduction factor) between the precipitation and the runoff volumes. None of the observations in the Frejlev catchment indicate that the runoff depends non-linearly on the precipitation, i.e. on the soil infiltration rate (Appendix C). This is due to very little runoff contributions from the semi-pervious and pervious surfaces in the Frejlev catchment. Therefore, the simple approach is applied throughout the thesis.

The physical structure of an urban drainage model is defined in parameters specific for the catchment in question, e.g. pipe dimensions, manhole coordinates, surface geometry, etc. These values are implemented deterministically, as it is decided to have confidence in the correctness of the values. Although slight uncertainties may be present in the technical maps, drawings, etc. that are used to digitalize the physical structure. But this is considered of minor importance.

On the contrary, the uncertainties related to the rainfall input data are much larger. Applying a synthetic rainfall input, as presented in the first stochastic approach (Paper IV and V), shows that some uncertainty is linked to the conceptualisation of the rain. Furthermore, some of the dynamics of the rain are neglected when applying the synthetic rainfall input. Another source of uncertainty is present with regards to whether the observed rain data, on which the parameterisations of the synthetic events are conducted, are representative for the catchment in question. This is included in Paper V, by sampling both bias as well as the dispersion between the Svenstrup rain gauge (located few kilometres from the catchment) and the Frejlev South rain gauge. Finally, there is a great extent of uncertainty related to the spatial variability of the rainfall input. In the presented stochastic approach applying a synthetic rainfall input, the input is assumed uniformly distributed over the catchment. This source of uncertainty is to some extent handled in the sampling interval of the hydrological reduction factor.

Real historical rain series applied as model input, Paper II, III, VI and VII, are associated with some of the same uncertainties as the synthetic rain. Especially the geographical variability of historical rainfall is a significant source of uncertainty. The geographical variability is often neglected and data from one rain gauge is assumed to represent the whole catchment. To some extent, this is a valid assumption in the Frejlev case, as the catchment is rather small. In Appendix B it is shown, applying an extrapolating correlation analysis based on 9 gauges within a radius of 25 km, that the average characteristic correlation length of event rain depths is approx. 40-50 km for summer events (convective rainstorms) and approx. 60-80 km for winter events (frontal rainstorms). Doing the same analysis based on event peak intensities the correlation length is approx. 30-40 km for both summer and winter events. The Frejlev catchment, being approx. 1.5 x 1 km, is therefore not represented

by a significant rainfall variability. However, some minor dispersion between the two local rain gauges in Frejlev is observed (Appendix C). The GLUE analysis (Chapter 10.2 and Paper VI) shows significantly better prediction of observed flow time series when applying an average of rainfall recordings from two gauges, compared to using recordings from only one. However, examining the predicted extremes, no significant difference between the two approaches is proven. In the stochastic modelling approaches the geographical variability is to some extent incorporated in the uncertainty of the hydrological reduction factor (based on the corresponding rainfall-runoff measurements in the catchment). This is done non-dynamically so that the rainfall is assumed to be uniformly distributed over the catchment in every event. However, a variation from event to event is implemented. This might influence the prediction of maximum water levels locally in the drainage system as some of the dynamics are neglected but, with regards to the runoff volumes and overflow volumes, the error introduced is insignificant.

Another aspect of the rainfall input uncertainty is the estimation of the return periods. Traditionally, the maximum return periods are estimated according to the length of the rain series. Applying short series might lead to an under-estimation of the return periods, and potentially also an over-estimation. In order to include this uncertainty, relationships between the maximum water levels as well as overflow volumes and characteristic rainfall parameters are derived. The return periods of the characteristic rainfall parameters (event peak intensity, depth and duration) can be assessed quite accurately applying a Pareto model based on statistics from several Danish rain gauges. The return periods of maximum water levels and overflow volumes are thus assessed applying the return periods based on the return periods of the characteristic rainfall parameters. Hereby, it is possible to generate return periods which are larger than the rain series length, and thereby reduce this source of uncertainty.

With concern to the calculation parameters uncertainties it is shown that the parameters governing the temporal flow variations, e.g. Manning numbers, headlosses, surface concentration times, etc. have little influence on the extremes, however, some influence in prediction of observed flow time series. The all-important calculation parameter is the hydrological reduction factor, as this parameter controls the runoff volumes. The statistics of the reduction factor show a mean value of approx. 0.5, i.e. a 50 % runoff contribution from the impervious surfaces in the Frejlev case. However, the factor is also shown to have a large dispersion, as it assumes values in the range from nearly 0 to 1. Occasionally, the reduction factor assumes values larger than 1. This is due to a smaller registration of rain in the gauge than in the rest of the catchment and indicates a geographical variability. This means a variation in the predicted runoff volumes of up to 100 % of the mean, which is very decisive for both maximum water levels as well as overflow volumes. It would however be interesting to see if the dispersion might be reduced if a more distributed rainfall is applied. The low mean value of the reduction factor emphasizes the importance of model calibration on runoff measurements. If a modeller chooses a standard reduction factor of maybe 0.7 - 0.9, the mean volume error might be significant - at least in catchment types similar to the one applied in this study. Whether the model is calibrated with regards to runoff volumes is for that reason considered as one of the most uncertain parts of an urban drainage model.

Applying the different approaches and investigations presented in the thesis it is shown that urban drainage models are uncertain to a great extent, especially on large return periods of maximum water levels and combined sewer overflow volumes. On low return periods, however, the predictions appear quite reliable. These results are based on a well-calibrated model setup of the Frejlev catchment, and it is evident that the uncertainties are significantly larger if the model in question is un-calibrated, as is the case with most models for non-research application.

Some methodologies have been proposed to handle the uncertainties, but the next step is to try to reduce the uncertainties further by increasing measurements on drainage systems.

## 11.2 Perspectives

This section presents suggestions for further investigations and improvement of the different simulation approaches applying the Frejlev catchment

As it has not been possible to do a model conditioning on the whole catchment, but only on down stream measurements of flow and overflow occurrence, it would be preferable to initiate a measuring campaign with water level gauges placed in different manholes in the drainage system. Hereby, it could be investigated if the assumption of global parameter values are valid or a more distributed model setup with local parameter values should be implemented in order to predict correct water levels upstream in the drainage system. Furthermore, more observation points could help to get a better understanding of the rainfall variability.

Moreover, it would be preferable to carry out a GLUE analysis with more than nine events in order to get more reliable posterior distributions. This may help reduce the prediction intervals of the long term Monte Carlo simulations.

The ongoing research in applications of weather radar data as input to urban drainage models is also an interesting subject to investigate further. A GLUE analysis similar to the one presented in this study but with radar data input may help to predict the observed flow time series more accurately. The prediction of flow time series may also be improved by better calibrations of the surface runoff models. This would require some local micro-hydrological measurements of surface runoff from sub-catchments, in order to get a more realistic input to the pipe flow models.

The FORM approach has shown to be very applicable in prediction of surcharge, flooding, and combined sewer overflow. More investigations in this methodology might create an applicable alternative to simple design methodologies such as the Rational Method, the Time-Area method, and models applying the Chicago Design Storm. This would require an analysis as the one applied in Paper V, but dealing with occurrence of surcharge/flooding instead of occurrences of combined sewer overflow. Furthermore, it would be interesting to

apply a spatially distributed rainfall input on the FORM approach, e.g. applying the spatial rainfall generator of Willems (2001).

Finally it would be preferable to investigate all of the proposed methodologies on different and preferably larger catchments, in order to find out whether the results are applicable elsewhere.

### 11.3 Recommendations

This section presents some general recommendations for design and analysis of drainage systems.

Based on this thesis a change in the current Danish design practice for small catchments is not recommended. It seems that both the former design practice (Spildevandskomiteen 1974) and the new proposed (Spildevandskomiteen 2005), in which new safety factors implementation of climate changes are presented, includes appropriate safety. Whether the selected safety factors are sufficient or insufficient in order to handle the climate changes will be an interesting topic of the future. It is, however, recommended to improve the practice of analysis, using modelling tools, when analysing large drainage systems. This study has presented various stochastic methods with the purpose of including uncertainties in model simulations. These are considered applicable in propagating uncertainties through the models, but are not recommended to be applied by consultants for non-research due to the simulation times. Even with the increase in computer power, it is not realistic to simulate thousands of hours on a single catchment.

The uncertainty in model simulations, however, could be exposed by the use of sensitivity analyses in order to expose some of the main uncertainties in prediction of maximum water levels in manholes and combined sewer overflows. This could, for example, be implemented by applying a range of values of the hydrological reduction factor, as this is clearly the most important parameter. In hindcast simulations it may also be preferable to do different simulations with different rain series in order to examine model results with regards to the sensitivity of the rainfall input. This is applied by Schaarup-Jensen et al. (2008).

The only way to get more reliable model predictions is by an improvement of inputs and parameters, which can only be obtained by further measurements in drainage systems (both on inputs and responses). More and longer rain series (or e.g. spatially distributed radar series) would increase the reliability of the rainfall input significantly. Furthermore measurements of flow, water level, overflow occurrences, etc. are necessary in model calibration. Flow measurements are quite comprehensive and expensive to perform, however Rasmussen et al. (2008a) have shown that the overflow registrations using on-off switches can be used to estimate values of the hydrological reduction factor in the same order of magnitude as applying flow measurements.

It would enhance model predictions remarkably if local estimates of parameter values were applied based on calibrations instead of general empirical and standard values.

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## Chapter 12

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## Appendix A

### Local rainfall statistics

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*This appendix presents statistical analyses applying recordings from three local rain gauges. The results are used to investigate spatial and temporal differences in rainfall observations.*

#### A.1 Introduction

In order to find potential differences in recordings between the gauges on different time scales, e.g. yearly, monthly or event based, different statistical analyses are conducted and characteristic correlations are derived. Furthermore the extreme statistics between the three gauges are investigated. Geographical patterns and the spatial variations of the rainfall are to some extent presented in this appendix, but presented in detail in Appendix B.

The purpose of the appendix is to justify the choice of rainfall input to the urban drainage models, in terms of which gauge or gauges to choose in order to obtain the most reliable rainfall input using the available data. The analysis is based on 9 years (1997 – 2006) of high temporal resolution rainfall recordings from the three Danish rain gauges Frejlev South (no. 20456), Frejlev North (no. 20458), and Svenstrup (no. 20461), Figure A.1.

#### A.2 Definitions

The rainfall data analysed in this appendix is founded on definitions from The Danish Water Pollution Committee under the Danish Engineering Society as well as the Danish Meteorological Institute. The recordings are all based on the RIMCO rain gauge, which is used in Denmark (DMI 2004, 2006, 2007; Spildevandskomiteen 1999, 2006).

The event time series has a temporal resolution of 1 minute, and a rainfall event consists of a minimum of two registrations (0.2 mm of rain per registration) within a period of 60 minutes. The first registration is assigned to the first minute, and the event ends one the minute on the last registration. If the time between registrations is more than one minute, the rainfall intensity is calculated by distributing the registration over the period of time between registrations (DMI 2004, 2006, 2007). An example of a recorded rain series is shown in Figure 7.6 and A.2.

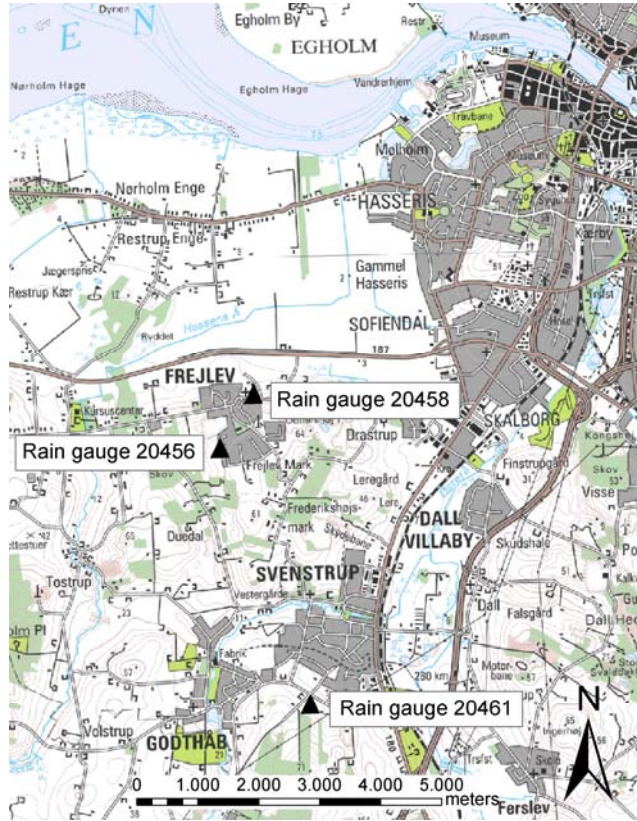


Figure A.1 Map of the Frejlev area with three rain gauges.

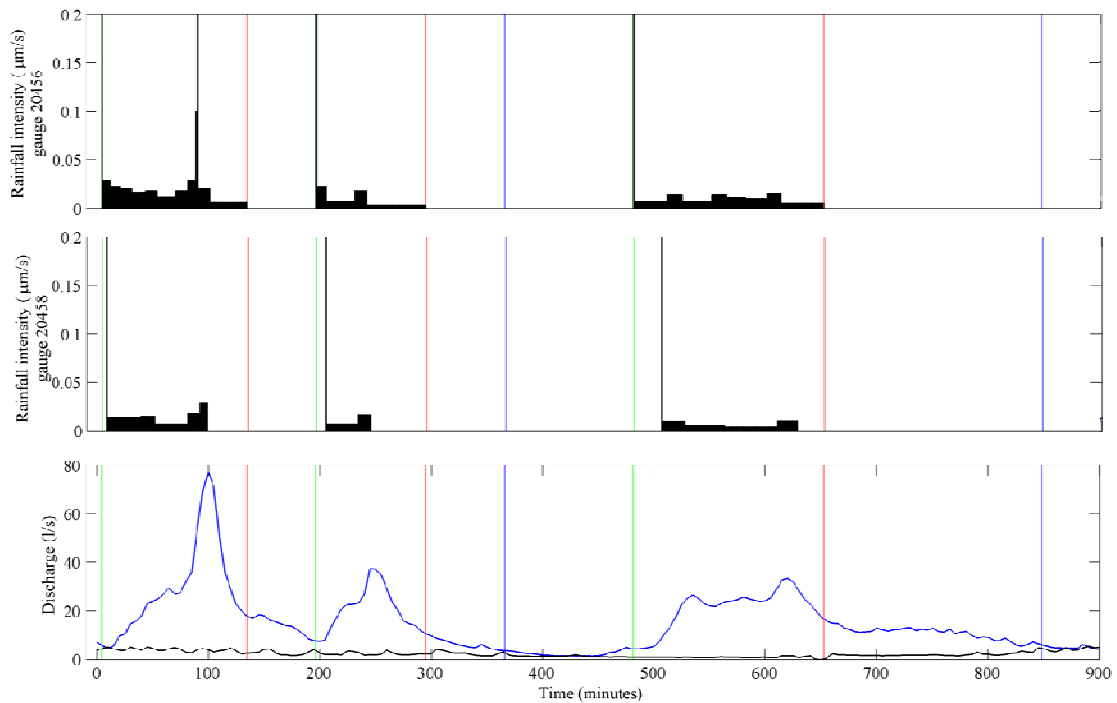


Figure A.2 Definition of runoff events. Vertical green, red, and blue lines match rain start, rain end, and runoff event end respectively. The blue time series is the observed flow and the black the dry weather flow 5 days prior to the event.

The recordings are based on the raw measurement data, and are not rectified in any way. However, some manual quality control is carried out, e.g. by eliminating unrealistically high intensities and snowfall events.

In the context of comparing recorded rainfall with runoff measurements is advantageous to define runoff events instead of rainfall events, as presented in Figure A.2. The runoff event start is defined when either of the two rain gauges records the first registration. The runoff event end is defined when the discharge is equal to the dry weather flow one or more days prior to the event.

In order to compare characteristic rainfall parameters (e.g. event depths, peak intensities, or durations) on an event by event basis, some methods and definitions (e.g. of travel time of rainfall) are presented in Appendix B.2.

### A.3 Methodology

Traditional linear regression techniques minimize the least square error (MSE) of the residuals (Figure A.3):

$$MSE = \min \left( \sum_{i=1}^N (y_i - \hat{y}_i)^2 \right) \quad (A.1)$$

This concept gives preference to the  $y$ -values compared to the  $x$ -values, and exchanging  $x$  and  $y$  does not represent the reciprocal slope of the regression line. In order to weight the  $x$ - and  $y$ -values equally the concept of orthogonal regression (Figure A.4) is introduced, in which the diagonal residuals (orthogonal to the regression line) are minimized using least squares:

$$MSE = \min \left( \sum_{i=1}^N (d_i)^2 \right) \quad (A.2)$$

By this it is possible to do linear regression with no preference to whether the values are assigned to the abscissa or the ordinate.

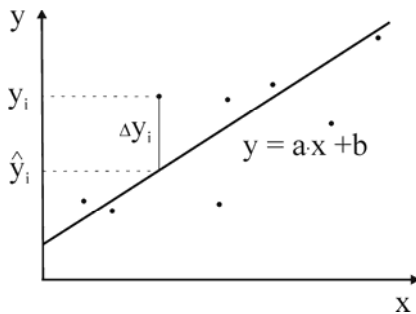


Figure A.3 Concept of traditional linear regression with dependent variable ( $y$ ) and independent variable ( $x$ ).

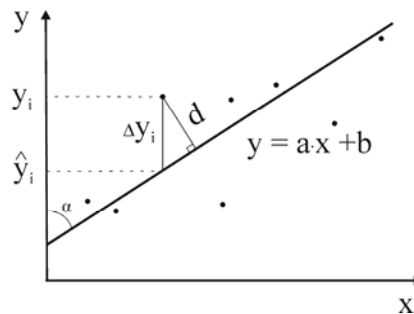


Figure A.4 Concept of orthogonal regression.

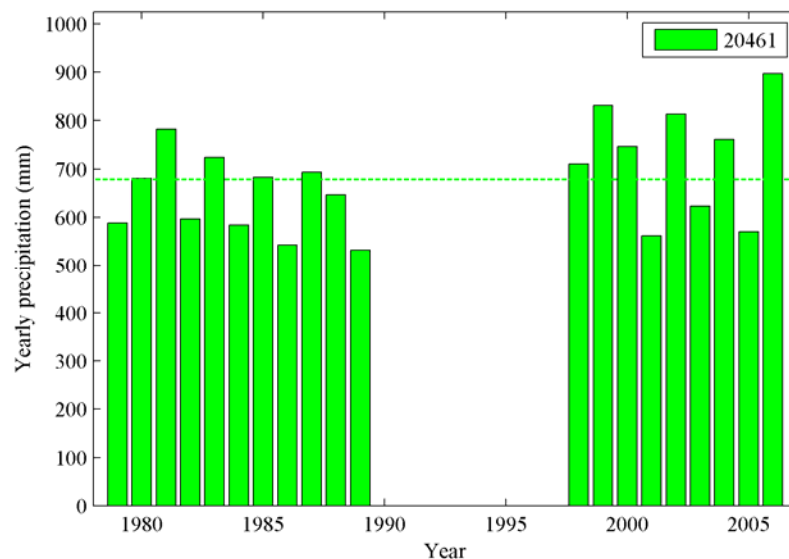
In the regression analyses, a t-test for the regression line slope is performed. This is presented using the  $p$ -value, which defines the probability of the regression line slope being equal to  $a$ . (e.g.  $p_{a=1}$  corresponds to the probability of the slope equals 1)

#### A.4 Yearly and monthly precipitation statistics

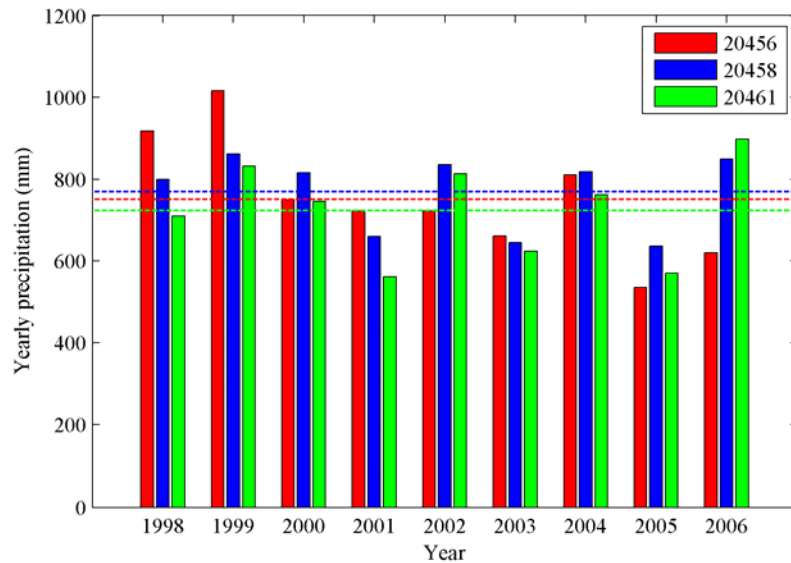
The Svenstrup rain gauge (no. 20461) has the longest time series of the gauges close to the Frejlev catchment as the measurements have been conducted since 1979. However, no measurements were conducted from 1990-1997, which gives a total length of the times series of 20 years (Figure A.5). During the 20 years 4875 events are recorded.

In order to compare the yearly precipitation measured by the gauges closest to the Frejlev catchment a bar plot of the total yearly precipitation is shown in Figure A.6.

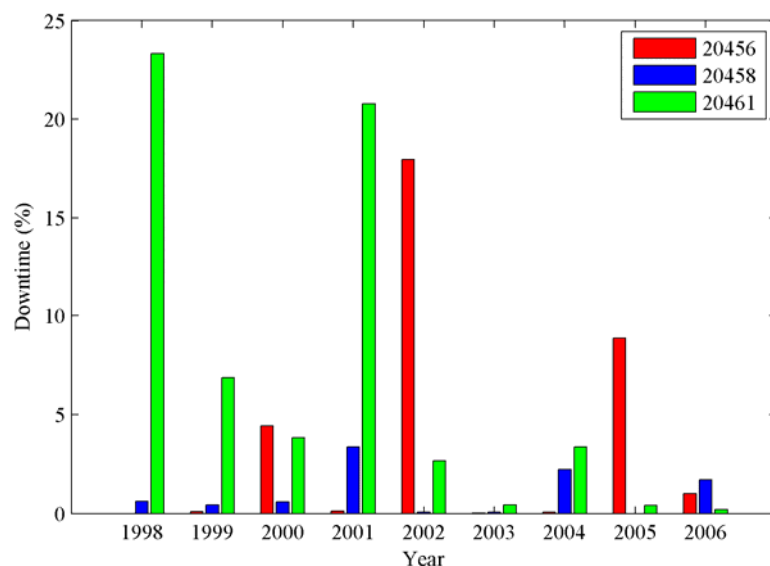
In order to correct the accumulated yearly precipitation due to possible downtime of the gauges, defects, and loss of data connection (Figure A.7), the precipitation in the closest gauge is calculated during downtime and added the yearly precipitation of the current gauge (Figure A.8).



*Figure A.5 Accumulated yearly precipitation from the Svenstrup (no. 20461) rain gauge 1979-2006.*



*Figure A.6 Accumulated yearly precipitation based on registrations in each of the three gauges (non corrected data).*



*Figure A.7 Yearly specification of downtime in percent.*

There are some deviations between the yearly accumulated rain in the three gauges, especially the gauge 20456 has recorded more rain during the two initial years (1998 -1999): From 2000 to 2004 approximately equal yearly precipitation is observed, whereas in 2005 and 2006 gauge 20458 has recorded significantly more than gauge 20456. The Svenstrup gauge (20461) has a significantly smaller yearly mean than the two gauges in Frejlev.

Whether the deviation between the gauges is due to systematic errors or a change in local wind conditions during the recording period is unknown, but will be investigated further in section A.6.

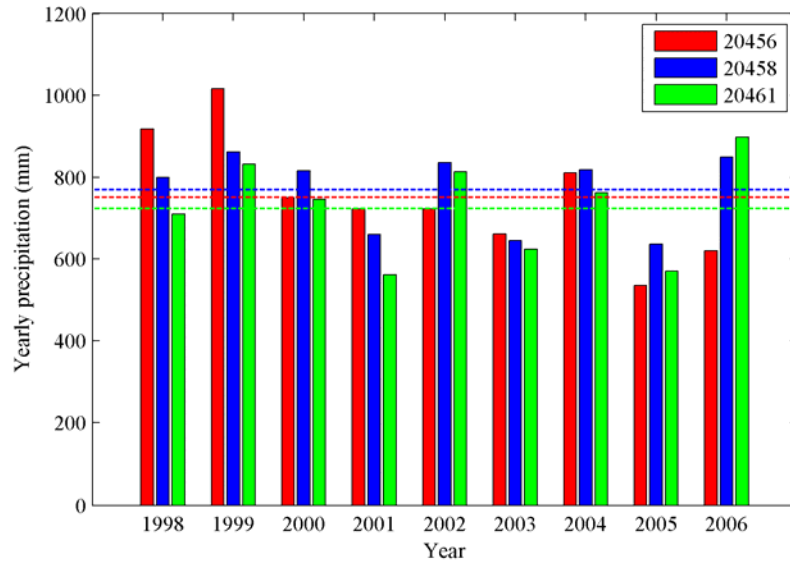


Figure A.8 Accumulated yearly precipitation corrected for downtime.

In the following it will be investigated, using linear regression, if the yearly tendencies are present in monthly statistics as well (Figure A.9 and Figure A.10)

Studying the scatter plot in which the whole time series of monthly precipitation of the Frejlev gauges are compared (Figure A.9), it is obvious that more rain is recorded in gauge 20456 compared to 20458 as in the yearly statistics. Dividing the time series in two periods (Figure A.10) it is obvious that there is a shift between the two gauges as 20456 has recorded the most in the period 1998-2003 and 20458 has recorded the most in 2004-2006. In order to investigate if these tendencies are also present in a smaller time scale an analogous analysis is carried out in the following section, using rainfall event statistics.

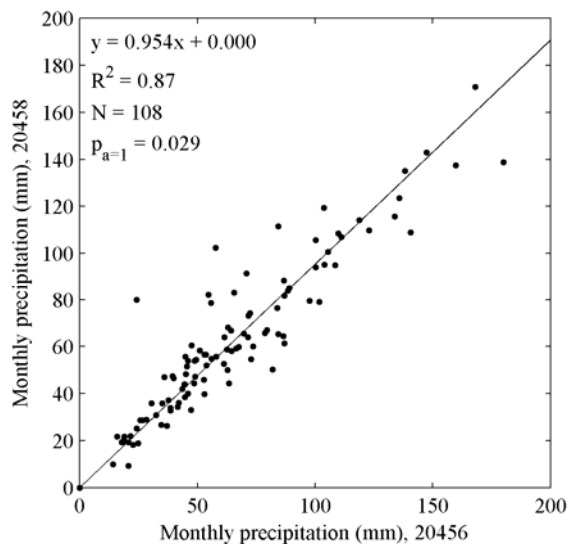


Figure A.9 Monthly precipitation of the two gauges in Frejlev in the period 1998-2006 (based on the data record corrected for downtime).

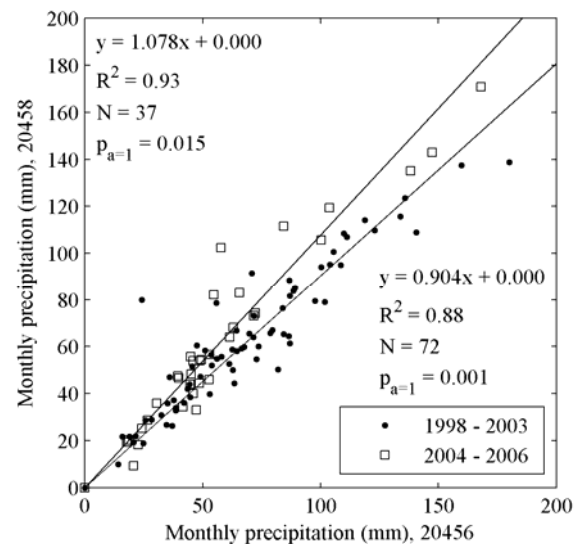


Figure A.10 Monthly precipitation of the two gauges in Frejlev divided in periods before and after 2004 (based on the data record corrected for downtime).

## A.5 Rainfall event statistics

Following regression plots are presented: gauge 20456 versus 20458, all data (Figure A.11); gauge 20456 versus 20458, divided in two periods (Figure A.12); gauge 20456 versus 20461, all data (Figure A.13); gauge 20458 versus 20461, all data (Figure A.14).

Studying the rainfall event records, again it is obvious that 20456 has recorded the most in the period up to 2004, and as it was the case with the yearly and monthly statistics the magnitude is approx. 10 % more. However, studying the rainfall event statistics there is no indication of a shift between the gauges in the period after 2004, which possibly has to do with few large events in the regression.

On event scale 20461 has recorded in the magnitude of 10 % less than the two Frejlev gauges during the whole year. Comparing, Figure A.11, A.12 and A.13 a correlation between the distance between the gauges (Figure A.1) and the dispersion in the data can be observed, that is the larger the distance between the gauges, the larger the scatter around the regression line. This correlation is also present in the  $R^2$  values, as it decreases with the distance between the gauges. This is investigated further in Appendix B.

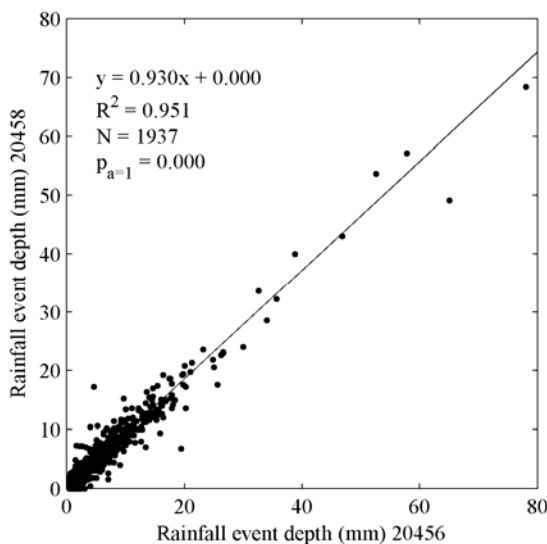


Figure A.11 Rainfall event precipitation in 20456 vs. 20458 in the period 1998-2006.

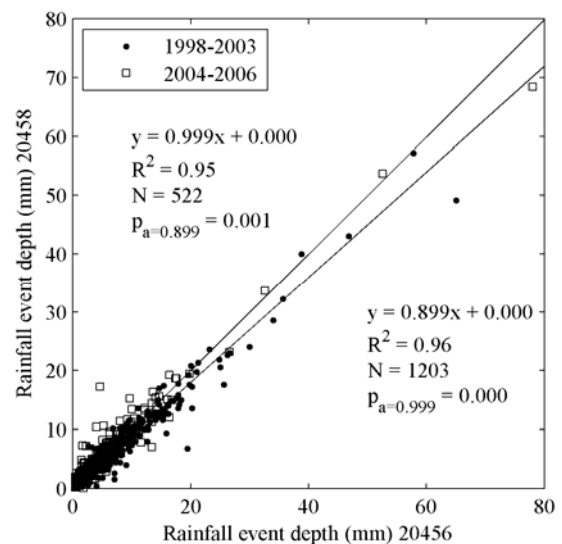
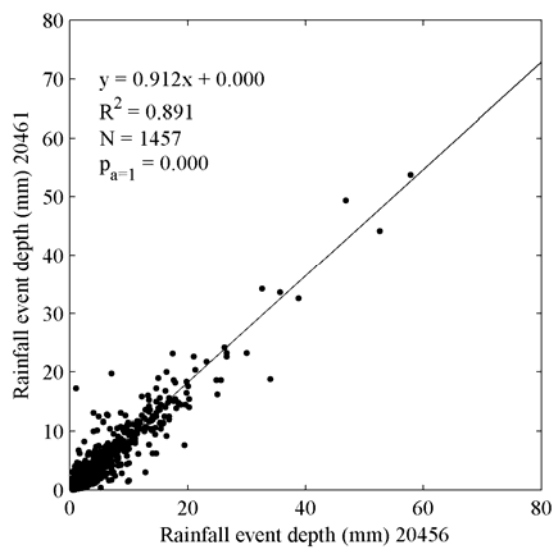
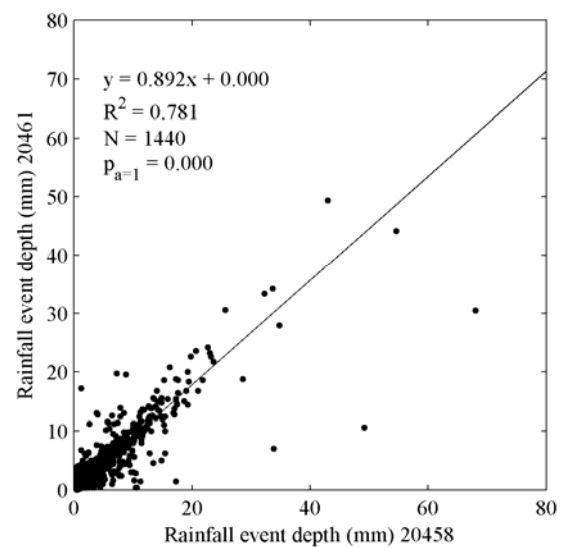


Figure A.12 Rainfall event precipitation in 20456 vs. 20458. The time series are divided in periods before and after 2004.





*Figure A.13 Rainfall event precipitation in 20456 vs. 20461 in the period 1998-2006. Orthogonal regression is applied.*



*Figure A.14 Rainfall event precipitation in 20458 vs. 20461 in the period 1998-2006. Orthogonal regression is applied.*

## A.6 Wind correction

The data analysed in the previous sections are non-corrected with regards to wind and shelter effects. Recorded rain gauge data can however be corrected on different time scales as presented in e.g. Vejen et al. (1998), Vejen (2000, 2005), and Allerup et al. (1997). Doing these corrections requires high temporal resolution wind data recorded close to the rain gauges in order to correct the rain series. Thus, it is not possible to do corrections in this investigation as no wind gauges are situated within a 10 km radius of the rain gauges. In order to estimate if the difference between the recordings in the three gauges is due to local wind effects, some reflections on wind correction is presented in this section, however without doing the actual corrections.

The empirical correction method presented in Allerup et al. (1997) includes wind speed, height angle (Figure A.15) in eight directions and the rainfall intensity. The method includes both rain and snow, but the latter is not important in the context of this project. A correction coefficient is multiplied the accumulated precipitation or the individual rainfall intensities. An example of the correction coefficient as a function of wind speed and rainfall intensity is shown in Figure A.16. It is obvious that the greatest corrections are when the wind speed is large and the rainfall intensity is low. The wind speed is empirically reduced by the height angle, such that the wind is not changed if the gauge is well-protected, but reduced or increased if the gauges is either unprotected or over-protected, cf. Table A.1. In Figures A.17-A.19 the height angle for the three gauges is shown for different periods. It is obvious, by the mean value, that gauge 20458 is unprotected during the whole period. Both 20456 and 20461 are moderately protected during the period, however 20456 processing towards a well-protected. It is hereby plausible that the difference between the gauges is due to wind effects.

The Danish Meteorological institute has informed that gauge 20456 was exchanged in January 2004, due to fireworks destruction New Years evening. Whether the replacement of the gauges has influenced the results, potentially due to another calibration is here unsaid.

Table A.1 Classification of height angles Vejen (2005).

	Height angle
Well-protected	$19^{\circ} < \alpha \leq 30^{\circ}$
Moderately protected	$5^{\circ} < \alpha \leq 19^{\circ}$
Unprotected	$0^{\circ} < \alpha \leq 5^{\circ}$
Over-protected	$\alpha > 30^{\circ}$

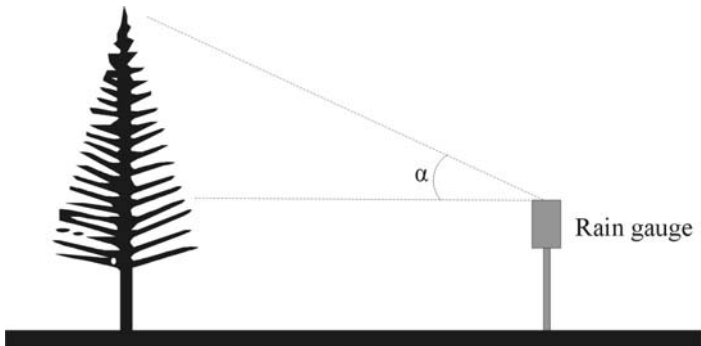


Figure A.15 Definition sketch of the height angle.

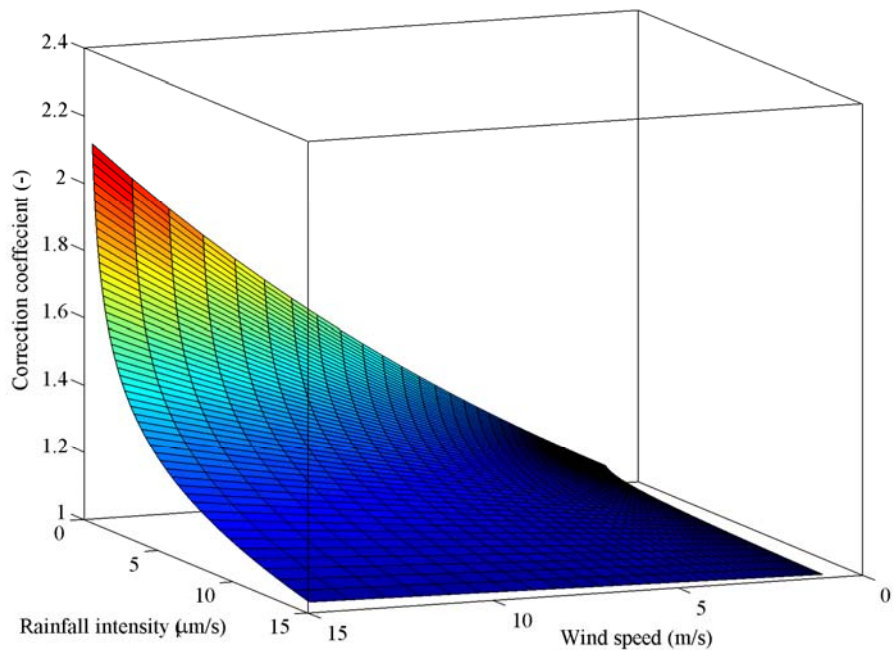


Figure A.16. The wind correction coefficient as a function of wind speed and rainfall intensity.

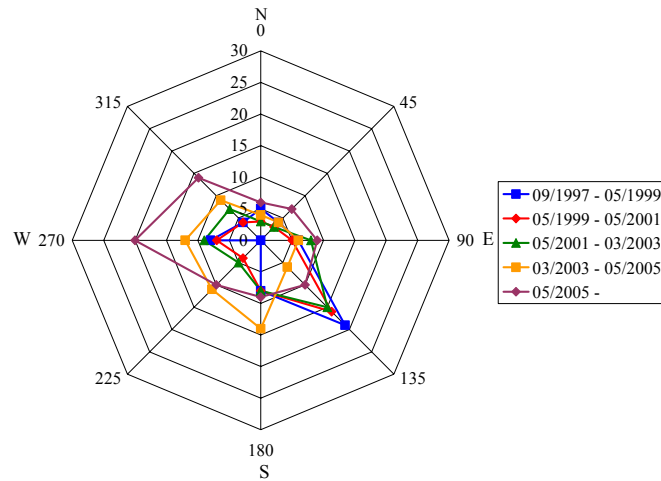


Figure A.17 Height angles and directions for 20456. The mean height angle for the whole period is 9.6.

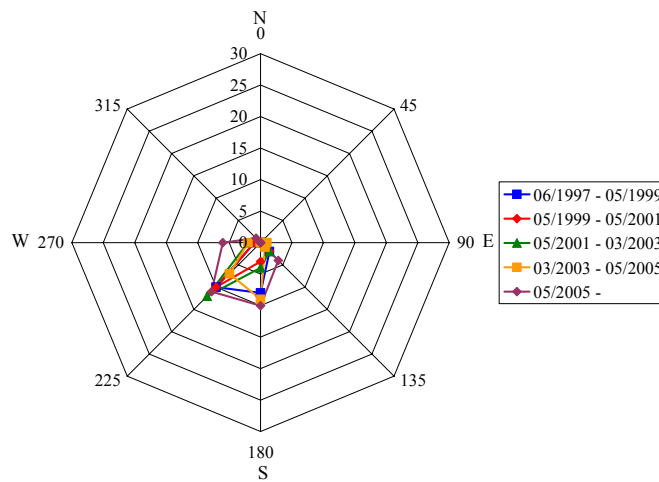


Figure A.18 Height angles and directions for 20458. The mean height angle for the whole period is 4.2.

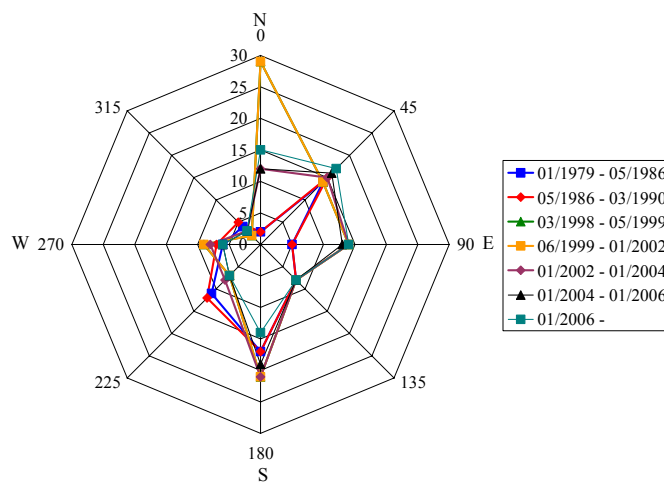


Figure A.19 Height angles and directions for 2046. The mean height angle for the whole period is 12.2

## A.7 Runoff event statistics

Using the runoff event definition (Section A.2) is advantageous in the study of rainfall-runoff relationships (Appendix C). In order for these statistics to be of high quality it is important that the same rainfall statistics can be derived from both the rainfall event definitions and the runoff event definitions. The runoff event statistics are based on quite smaller set of data due to downtimes and problems with the flow gauges.

In order to test the correlations found in the previous section an example is shown. The equivalent to Figure A.11 using runoff event definition is shown in Figure A.20. The regression line slope using the rainfall event definition is 0.93 and using runoff event definition 0.90. These are inside an acceptable range, even though the probability of the slopes being the same is 0.0002. Similar results are found comparing the other combinations of rainfall event and runoff events.

In figures A.21-A.23 the correlation between the runoff event 10 minute averaged peak intensity are calculated for the three gauges in different combinations. It is obvious that, the larger the distance between gauges the larger the dispersion of the peak intensities. The dispersions are much larger than the accumulated rainfall during the runoff event. Averaging over other aggregation levels (durations) show the same tendencies. This is investigated further in Appendix B.

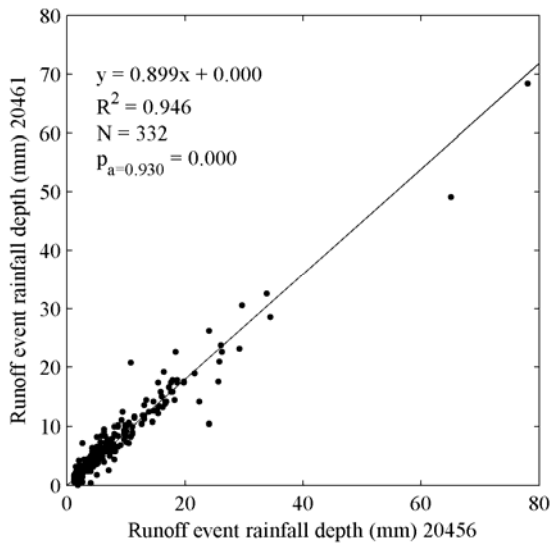


Figure A.20 Runoff event depths in 20456 vs. 20458 in the period 1998-2006.

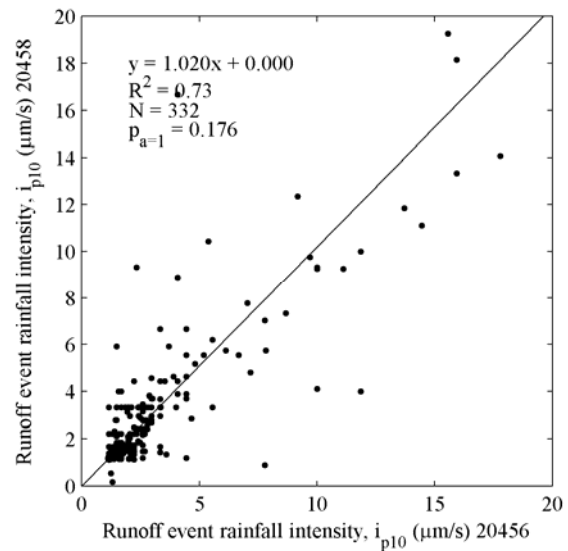


Figure A.21 Runoff event 10 min peak intensities in 20456 vs. 20458.

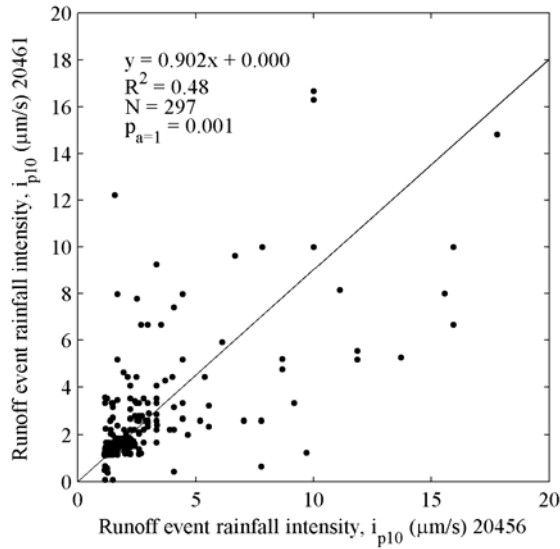


Figure A.22 Runoff event 10 min peak intensities in 20456 vs. 20461.

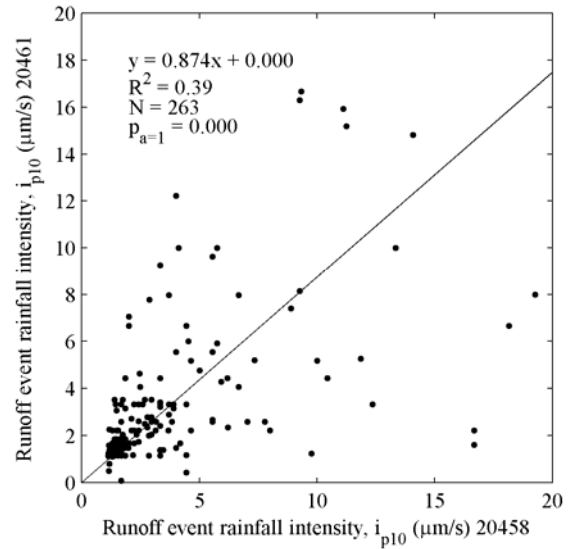


Figure A.23 Runoff event 10 min peak intensities in 20458 vs. 20461.

## A.8 Conclusions

Some bias between the rainfall recordings in the three gauges is observed, which probably is due to local wind effects around the gauges. It is however not possible to correct the data for these wind effects as local wind data is not available, but since the bias is only about 10 % the consequences are not considered vital.

Due to the spatial variations of the rain some dispersion on individual events between the gauges are also observed. The dispersion is quite small considering the accumulated rainfall depth per event, but large when comparing the event peak intensities. The dispersions of the rain depth are implemented in Paper V.

Furthermore the same characteristics are found for both rainfall events and the defined runoff events, hence it is possible to use the statistics based on rainfall events in analysis of runoff. This is done in Paper IV, V, and VII.

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## Appendix B

### Regional rainfall statistics

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*Based on data from nine rain gauges within the Municipality of Aalborg, the following appendix introduces an approach to find a characteristic correlation length of rain storms, in order to investigate the spatial rainfall variability over the Frejlev catchment.*

#### B.1 Introduction

Using real recorded time series as rainfall inputs to urban drainage models, one of the main concerns are if the recorded data from one rain gauge are representative for the whole catchment. In this appendix it will be investigated if a characteristic *correlation length* can be derived from data statistics using nine rain gauges within a mesoscale radius (0 – 25 km). These gauges are all situated within the Municipality of Aalborg (Figure B.1). The characteristic correlation length can be used to determine the importance of spatial rainfall variability, that is, if it is necessary to use a spatial distributed rainfall input to the model in question or if it is sufficient to use a point measurement. Moreover, the analysis provides useful information of the spatial extent of rain storms during the change of seasons.



Figure B.1 Map of rain gauges in the Municipality of Aalborg.

*Table B.1 Upper triangular matrix: diagonal distance between gauges; Lower triangular matrix: latitudinal distance between gauges. All distances are in kilometres. The right column show the running periods.*

gauge no	20456	20458	20461	20307	20309	20304	20298	20212	20211	Period
20456	0	1.9	3.8	6.3	9.6	9.8	11.1	17.2	20.7	1997-2006
20458	0.0	0	5.7	4.8	8.2	8.9	11.3	16.1	19.0	1997-2006
20461	1.1	1.1	0	9.5	12.2	11.7	10.8	19.2	23.7	1979-2006
20307	3.0	3.0	1.9	0	3.6	5.1	9.8	11.5	14.3	1998-2006
20309	6.0	6.0	4.9	3.0	0	2.7	9.0	8.0	11.5	1998-2006
20304	8.0	8.0	7.0	5.1	2.0	0	6.3	7.5	13.0	1990-2006
20298	11.1	11.2	10.1	8.2	5.2	3.1	0	11.3	18.7	1999-2006
20212	13.0	13.0	11.9	10.0	7.0	5.0	1.9	0	8.4	2000-2006
20211	8.8	8.9	7.8	5.9	2.9	0.8	2.3	4.1	0	1979-2006

Besides the two gauges in Frejlev (20456 and 20458) and Svenstrup (20461) following gauges are included in this survey: Aalborg WWTP West (20307), Nørresundby (20309), Aalborg Østerport Pump Station (20304), Gistrup (20298), Vodskov (20212), Sulsted (20211).

The overall period investigated ranges from 1979 to 2006, however as gauges have different running periods, the period investigated is individual for each pair of gauges, so that the largest number of rainfall events are included in the correlation assessment. Downtimes of the individual gauges are taken into account, cf. Appendix A.4. In Table B.1 the diagonal and latitudinal distances between the gauges are presented. The latter is presented as the main wind direction in Denmark is from west to east. A correlation with both the diagonal and the latitudinal distance are thus expected.

In Denmark the summer period (May up to and including September) is dominated by convective rainstorms, whereas frontal rain dominates the winter period (November up to and including March). Convective rainstorms arises when overland warm raising air is cooled down and condensates. According to Ahrens (2007), convective rainstorms are in the mesoscale range (1-100 km). The frontal rain is caused by cold or warm fronts on the much larger synoptic scale (1000-2500 km). It is therefore expected that the correlation length of convective storms (summer rain) are smaller compared to the frontal storms (winter rain).

## B.2 Methodology

The analysis is based on the rainfall event definition from the Danish Meteorological Institute (Appendix A.2). The correlation between two gauges is found by comparing the rainfall depth and peak intensities at different aggregation levels (durations over which the rainfall intensities are averaged) in the two gauges event by event. It is presumed that the rain moves with a minimum of 1 m/s. Using this velocity, the maximum travel time is calculated by applying the diagonal distances (Figure B.1). The maximum travel time is then subtracted the event start time and added the event end time in the first gauge, and for this period of time the rainfall depth in the second gauge is accumulated. Correspondingly, the

peak intensities are found by the maximum of the moving average (over the duration equivalent to the aggregation level) in each gauge. The minimum travel time is set to 1 hour, corresponding to the minimum time between events.

The correlation between gauges is calculated applying the correlation coefficient  $R^2$ . The correlation length, which is defined as the distance in space beyond which events are uncorrelated, can then be derived by plotting the correlation coefficients as a function of the distance between gauges. Gaussian (red lines in figures B.3-B.14), based on Willems (2001), and linear (blue lines in figures B.3-B.14) regressions are applied using least squares techniques in order to extrapolate the observation data such that the correlation length can be estimated.

### B.3 Literature review

Several authors have investigated the subject of spatial variability of rainfall and with different applications, e.g. Willems (1999, 2001), Willems and Berlamont (2002), Vaes (1999), Vaes et al. (2005), Pedersen et al. (2005), Mikkelsen et al. (1996), Madsen (1998, 2002), Einfalt et al. (1998a), and De Toffol et al. (2006). The most important results are presented in the following:

Mikkelsen et al. (1996) and Madsen (1998, 2002) have investigated large datasets from the Danish rain gauge network and found out that maximum rainfall intensities for different aggregation levels could be fitted to an exponential decay function. They found out that the correlation length depends very much on the intensity. Plots in Madsen (1998) show a correlation length of approx. 50 km on a 10 min. aggregation level and a correlation length larger than 300 km for 24 hour aggregation levels.

Vaes et al. (2005) refers to Mennes (1910) who presents a parabolic relationship between correlation and distance suggested by Frühling. A Gaussian relationship presented in Luyckx et al. (1998), in which an average standard deviation of 2.5 km is applied. This approximately corresponds to a correlation length of 15 km. In Vaes et al. (2005) the concept of correction coefficients are presented, and based on a well calibrated spatial rainfall generator (Willems 2001), different aerial correction coefficients are derived depending on aggregation level and rainfall intensity. The correction coefficients can be interpreted in the same way as the correlation coefficients in this appendix, however no minimum correction coefficient (corresponding to the correlation length) is presented.

### B.4 Results

Correlating the gauges two by two it is possible to produce a correlation matrix plot as shown in Figure B.2. The correlation matrix plot is only shown for the all year data processing using rainfall depths, but the plots of the winter and summer periods are similar.

By examining Figure B.2 and Table B.1 it is clear that the correlation decreases as a function of the distance from the gauges. In Figure B.3 and Figure B.4 the correlation coeffi-



cients are plotted against the diagonal and the latitudinal distances between gauges, respectively. Despite a quite dispersed scatter it is clear in both plots that the correlation decreases as a function of the distances. This is also the case for the summer and winter plots, figures B.5-B.6 and B.7-B.8, respectively.

Comparing the correlation lengths (extrapolating to the intersection with abscissa) found by different regression methods, there is very little difference with regards to whether the gauss or the linear fits are applied. However, using the diagonal distances produces better fits using the linear regression, whereas using the latitudinal distances the  $R^2$  values are larger with the Gaussian fit.



*Figure B.2 Scatter plots of rainfall depths recorded in the nine rain gauges. All subplots range from 0 to 80 mm. All year data.*

The relationships found are obviously averaged and there are individual rainfall events in which the gauges are not correlated at all (if rain is recorded in one gauge but not in the other). This can also be seen on Figure B.2. Correspondingly, events in which the rainfall depths are fully correlated are also present. In figures A.9-A.14 the same analysis, using peak intensities with different aggregation levels, are presented. The aggregation levels of 10 min and 360 min are shown.

Examining the results it is seen that correlation against the diagonal distances is better than using the latitudinal distances as the scatter is less dispersed. Thus, the rest of this analysis is based on correlations with the diagonal distances. The best fit of the presented is clearly the 10 minute peak intensity summer data as a function of the diagonal distance.

It is evident that the dispersion is larger compared to the plots with accumulated rainfall depth (Figures A.3-A.8), which also is seen in the values of the residual correlation coefficients in the plots. Due to the poorer fits there are less difference between all year, summer, and winter data. It was expected that the aggregation level of 10 min. would have a smaller correlation length than the 360 min. level. This is to some extent also the case, but the difference is not significant due to large dispersion.

It would be possible to conduct this analysis with more gauges, so that that better regression fits might be found. This could also reduce the uncertainty implemented by extrapolating the regression curves to the intersection with the abscissa.

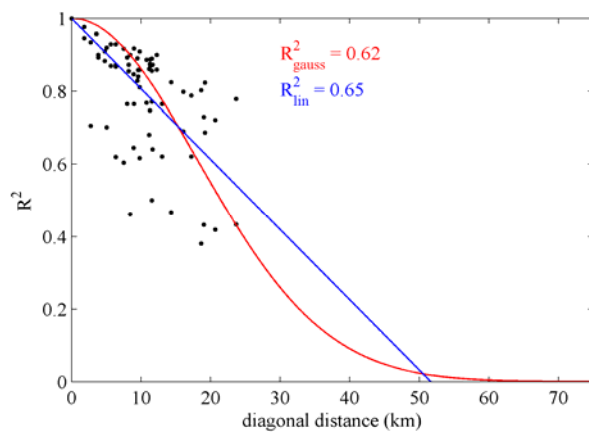


Figure B.3 Correlation coefficients of rainfall depths and the diagonal distance between gauges. All year data.

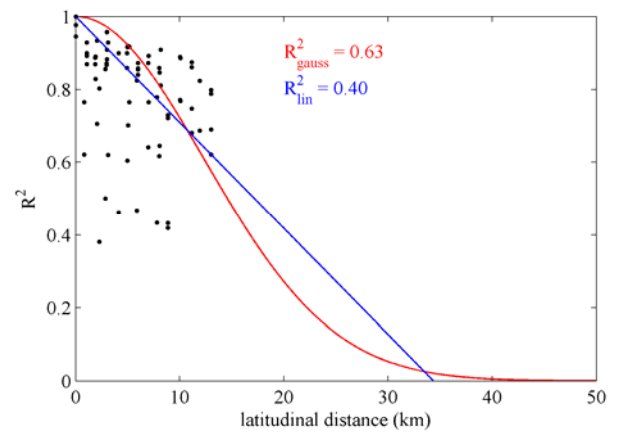


Figure B.4 Correlation coefficients of rainfall depths and the latitudinal distance between gauges. All year data.

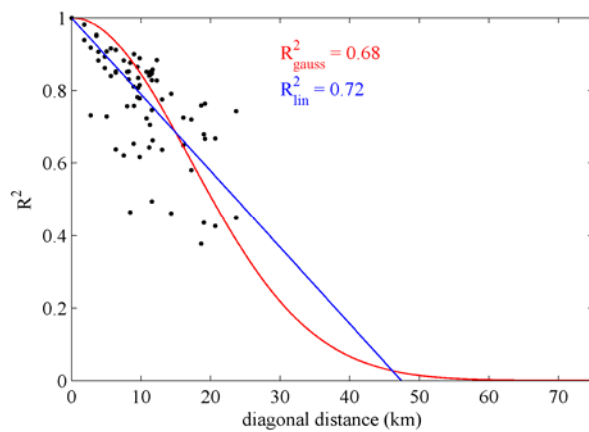


Figure B.5 Correlation coefficients of rainfall depths and the diagonal distance between gauges. Summer data.

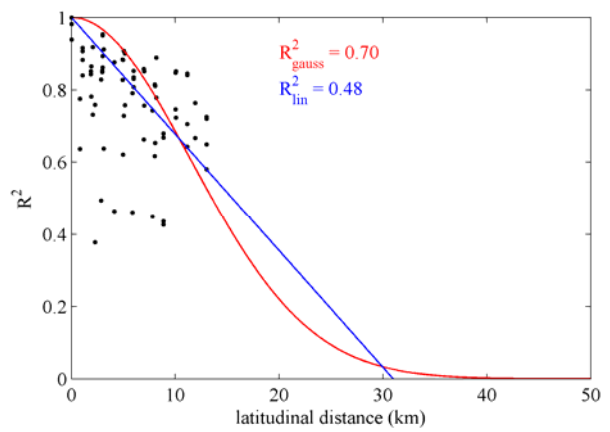


Figure B.6 Correlation coefficients of rainfall depths and the latitudinal distance between gauges. Summer data.

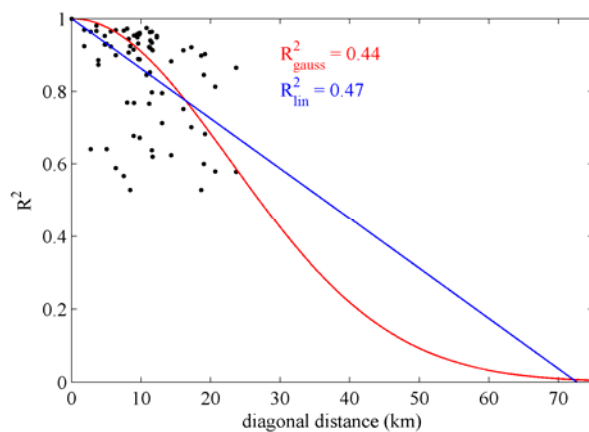


Figure B.7 Correlation coefficients of rainfall depths and the diagonal distance between gauges. Winter data.

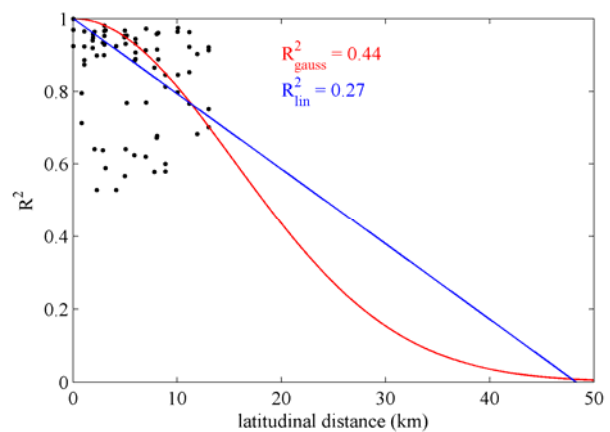


Figure B.8 Correlation coefficients of rainfall depths and the latitudinal distance between gauges. Winter data.

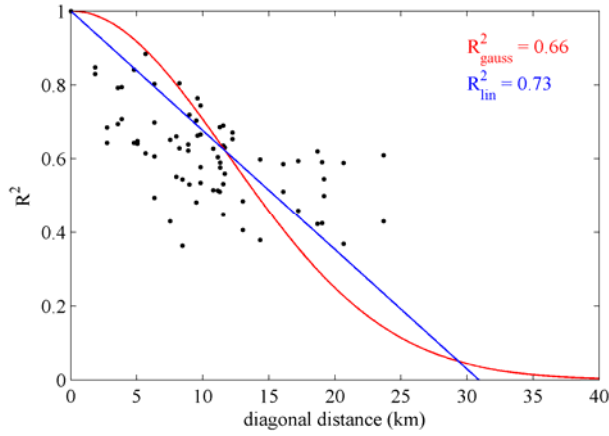


Figure B.9 Correlation coefficients of 10 minutes peak intensities and the diagonal distance between gauges. All year data.

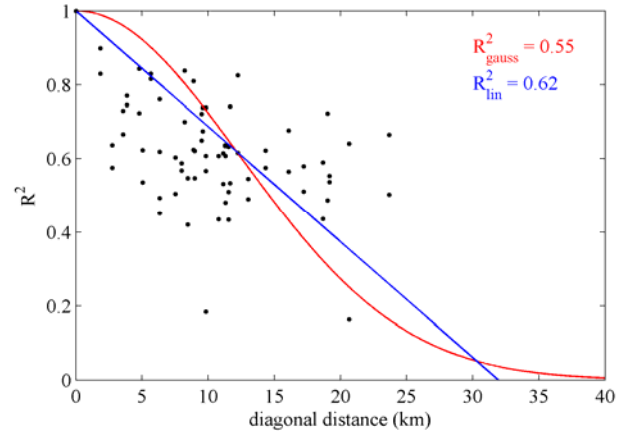


Figure B.10 Correlation coefficients of 360 minutes peak intensities and the diagonal distance between gauges. All year data.

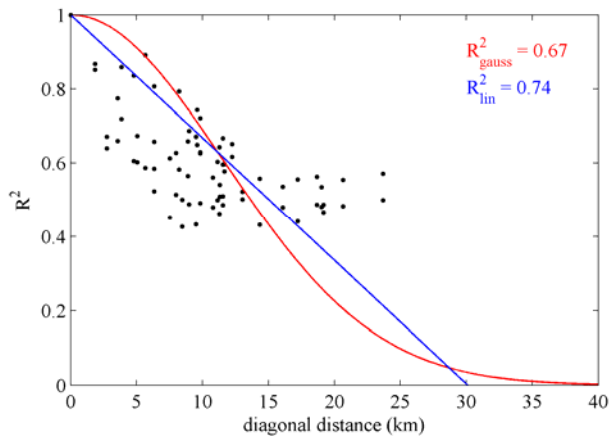


Figure B.11 Correlation coefficients of 10 minutes peak intensities and the diagonal distance between gauges. Summer data.

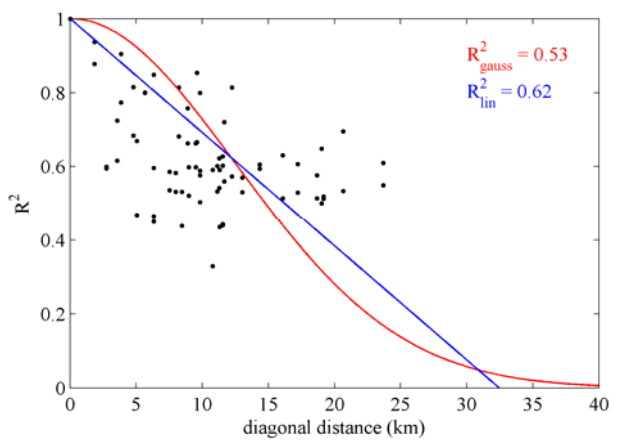


Figure B.12 Correlation coefficients of 360 minutes peak intensities and the diagonal distance between gauges. Summer data.

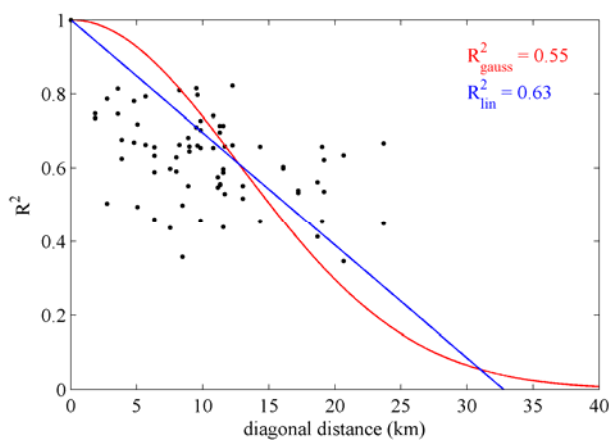


Figure B.13 Correlation coefficients of 10 minutes peak intensities and the diagonal distance between gauges. Winter data.

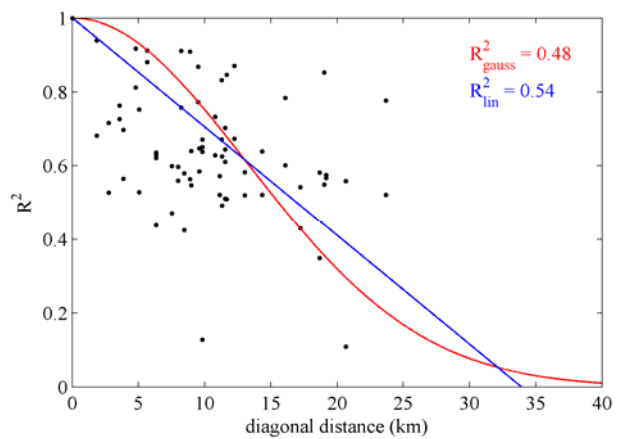


Figure B.14 Correlation coefficients of 360 minutes peak intensities and the diagonal distance between gauges. Winter data.

## B.5 Conclusion

The correlation length, defined as a characteristic distance in space beyond which no correlation to the origin point can be expected, is in the present analysis found to using the accumulated rainfall depths:

- 40-50 km for convective storms (summer events)
- 60-80 km for frontal rainstorms (winter events)
- 50-60 km as an average of all yearly storms

The correlation lengths based on the peak intensities are, in the range of 30-40 km, independent of both season and aggregation level. The values of the correlation lengths are very uncertain, due to the extrapolation of the poor fits.

One of the main reasons for this investigation was to find out if it was sufficient to model the Frejlev catchment with data from one rain gauge only, or if both gauges situated within the catchment should be applied - or even if neither was sufficient. The Frejlev catchment has a latitudinal extent of approx. 1 km and a longitudinal of approx. 1.5 km. Using the latter as a critical distance in the Frejlev catchment, residual correlation coefficients found applying the Gaussian regression (rainfall depth) corresponds to 0.997, 0.996 and 0.998 for the all year, summer and winter events, respectively. Correspondingly, the coefficients are 0.971, 0.968 and 0.979 applying the linear regression. Regardless of choice of regression method these correlations are very high. For comparison, the peak intensity residual correlation coefficients of the 10 min aggregation level using summer data is 0.992 and 0.950 for the Gauss and the linear fit respectively. However, if the fits is neglected and the data is interpreted directly, a correlation coefficients as low as 0.7 can be observed within a distance of only 3 km.

The correction coefficients found by Vaes et al. (2005) leads to a range of 0.96 – 1 (within the same distance) depending on the rainfall intensity in the Frejlev case.

Evaluating the large correlation coefficients, found in this investigation but also by other authors, a very little spatial variability should be present in the Frejlev catchment, and the potential errors of applying only one rain gauge is in a smaller order of magnitude than the measurement uncertainties itself. However, individual events where the spatial variability is significant might be found, e.g. in Paper VI, a significant better model conditioning is found using the two Frejlev gauges compared to applying only one. This is almost certainly due to spatial variability of the rainfall intensities.

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## Appendix C

### Corresponding rainfall-runoff statistics

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*The following appendix presents an analysis of corresponding rainfall-runoff measurements from the Frejlev catchment. Different correlations between the runoff and rainfall depths, intensities, dry weather periods, etc. are presented. The dataset is very essential in model calibration. Some of the results are also presented in Paper I and Paper II, but with a smaller dataset, therefore there might be minor inconsistencies in some predicted values.*

#### C.1 Introduction

Corresponding rainfall-runoff measurements are crucial in urban drainage model calibration in order to obtain reliable model outputs. Furthermore, the measurements can be used to gain more knowledge of urban hydrological processes which again can be used for model choice and constrictions (model conditioning).

Several authors have investigated urban rainfall-runoff relationships, e.g. Arnbjerg-Nielsen and Harremoes (1996a), Jensen (1990), Linde et al. (2002), Miljøstyrelsen (1997), Miljøstyrelsen (1990), Becciu and Paoletti (2000), Chen and Adams (2007), and Uggerby (2007). The dataset presented in this appendix is however much larger than the ones referred from the literature. This gives the possibility to investigate different hydrological processes which cannot be done significantly with a dataset containing only few corresponding rainfall-runoff measurements. Furthermore, it is possible to analyze and find characteristics for extreme events with large return periods.

#### C.2 The flow meters in Frejlev

The flow meters in the Frejlev catchment are presented in Chapter 3. Signals from the meters are logged non-time equidistant. During low flows the signal is logged every 20 seconds whereas the sampling interval is decreased during high flows. The signal from the meters is logged on a computer as currents (I) in mA (Figure C.1) and can be converted to flows (Q) in l/s using following relationship:

$$300 \text{ mm pipe: } Q = (I-4) \cdot 6.25 \quad (\text{l/s}) \quad (\text{C.1})$$

$$1000 \text{ mm pipe: } Q = (I-4) \cdot 218.75 \quad (\text{l/s}) \quad (\text{C.2})$$

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02-01-2006 00:02:27	4.226	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:02:47	4.225	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:03:07	4.226	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:03:27	4.219	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:03:47	4.218	4.000	4.000	00.000	00.000	00000000	
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02-01-2006 00:04:27	4.218	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:04:47	4.224	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:05:07	4.233	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:05:27	4.245	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:05:47	4.264	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:06:07	4.279	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:06:27	4.288	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:06:47	4.296	4.000	4.000	00.000	00.000	00000000	
02-01-2006 00:07:07	4.304	4.000	4.000	00.000	00.000	00000000	

Figure C.1 Example of a flow registration file

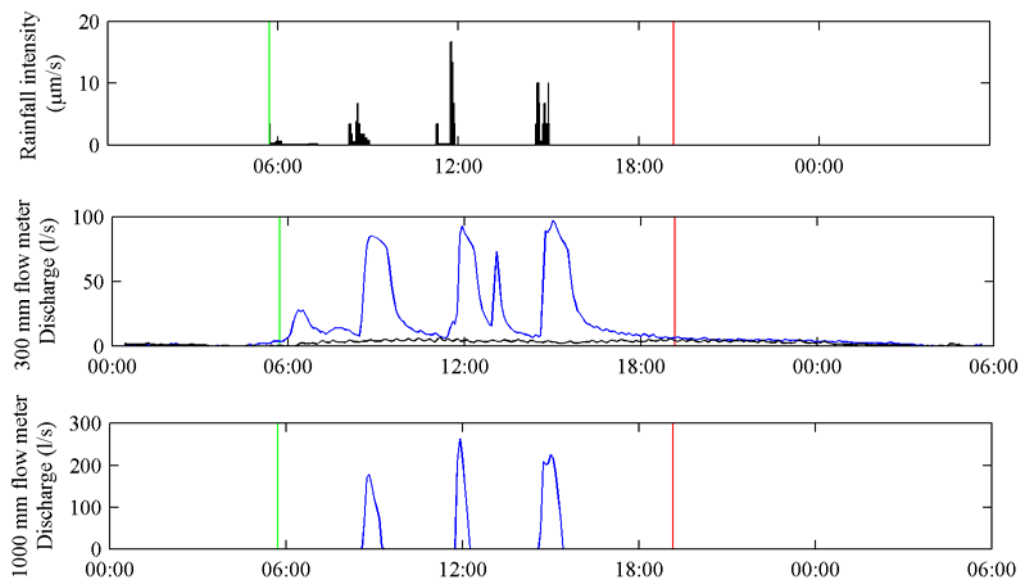


Figure C.2 Example of runoff event June 4-5, 1999. The blue line is the recorded flow and the black line is the dry weather flow 5 days before the event. The green and red vertical lines indicate start and end of the runoff event.

An example of an event of flow registration is presented in Figure C.2.

Due to different difficulties with both the flow meters and the recording equipment flow measurements are only available for roughly half of the 10 year running period. This corresponds to approximately 350 rainfall-runoff events with a rain depth larger than 1 mm.

### C.3 Methodology

In order to calculate part of the rain that runs off from the catchment, the flow time series is divided into runoff events as defined in Appendix A. By accumulating the flow per event from the two meters, subtracting the part of the flow which corresponds to the dry weather flow, and dividing by the impervious catchment area, the runoff depth (mm) can be determined.

In paper I, different definitions of the catchment area are investigated, but in this appendix the impervious catchment area is defined as all possible hard surfaces, that is road surfaces including pavements, car entrances, and roof surfaces including garages, tool sheds, covered and uncovered terraces. Using this definition the impervious area in Frejlev is calculated to 39 % of the total catchment area.

The dry weather flow, corresponding to the municipal waste water, is subtracted by accumulating the flow from a dry weather day in the same period as the event in question. A dry weather day is in this study defined when no rain has occurred for 12 hours. The dry weather day is found by examining the days prior to the event, and the first day with dry weather is chosen. One could argue that a mean of a dry weather day could also be implemented, but as seen in the example next, the dry weather flow represents a very little fraction of the flow during rain, which is why the choice of method is less important.

The accumulated flow in the event of Figure C.2 is 1332 m<sup>3</sup> and 976 m<sup>3</sup> for the two flow meters respectively and the dry weather flow originating from 5 days prior to the event corresponds to 164 m<sup>3</sup>. Applying an impervious area of 31 ha, this corresponds to a runoff depth of 6.9 mm. The rainfall depth in the period is 18.0 mm. An event specific hydrological reduction factor is calculated, ignoring the initial loss, by dividing the runoff depth by the rainfall depth to 0.38.

Applying this method assumes that the rain is uniformly distributed in space over the whole catchment, which obviously is a rough approximation. However by fixing the impervious contributing catchment area, knowing that this naturally also varies due to the spatial variability of the rain, the dispersion of the ratios between the runoff and the rain can be interpreted as a measure of the spatial variability. It is also well known that the pervious surfaces, e.g. grass areas, might contribute to the runoff during high intensive rainfall, which might lead to a larger contribution area than the impervious, this is again considered in the dispersion of the rainfall-runoff ratio. One could argue that a general runoff coefficient might be implemented, relating the rain to the total catchment area. It is however advantageous to relate to the impervious area as this method is used in e.g. the Time-Area method



(Linde et al. 2002). This method applies the hydrological reduction factor, defined as the slope of a linear regression line based on a number of rainfall depth and runoff depth observations (calculated using the impervious area). See figures C.4-C.13. The intersection with the rainfall axis corresponds to the initial loss. In basic hydrological theory it is stated that the runoff depends on the soil saturation, i.e. if the soil is unsaturated the runoff is smaller than if the soil is fully saturated. This is however neglected in the Time-Area method. Another method taking the soil saturation into consideration is the Horton infiltration method (Chow (1964)), in which the runoff decreases exponentially with the time. Pro and con arguments this method is discussed further in the next sections. The Time Area model and Horton's infiltration method is described in detail in Chapter 5.

## C.4 Results

Relationships between the runoff and rain per event are presented in Figure C.3, Figure C.4, and Figure C.5 using recorded rain from gauge 20456, 20458, and 20461 respectively. See figure A.1. The slope corresponds to the hydrological reduction factor ( $\phi$ ),  $R^2$  is the correlation coefficient,  $N$  is the number of runoff events,  $s_\phi$  is the standard deviation of the hydrological reduction factor, ignoring variance heterogeneity, and  $p$  is the probability of significance that the regression line slope equals  $a$ . If  $p$  is larger than the 0.05 significance level the null-hypothesis of equal regression lines is accepted and on the contrary the null-hypothesis is rejected if  $p$  is less than 0.05. Furthermore, the 95 % confidence interval of the regression coefficients are also shown in the figures.

The difference of the hydrological reduction factors found in Figure C.3, Figure C.4, and Figure C.5 corresponds somewhat to the difference in the recorded rain as presented in appendix A. This is probably due to wind effects around the gauges. The regression lines are just on the threshold of being significantly different, using a 5 % significance level, so the statistic basis is a bit too small to conclude that the hydrological reduction factor varies depending on the choice of rain gauge. As to the initial loss there is no significant difference between the observed values.

The dispersions around the regression lines are quite large as shown in the  $R^2$  and  $s_\phi$  values. The flow measurements are considered quite reliable, so this dispersion is considered as a result of spatial rainfall variability (i.e. one rain gauge is not representative for the whole catchment). This supports the statement that the dispersion is larger applying gauge 20461, which is the gauge with the greatest distance from the catchment. There are even events situated above the bisector which indicates that more runoff than rain is observed, this is either because of a high intensive rain in which the contributing area is larger than the impervious area (examined further in Figure C.9 and Figure C.10), or the fact that the rain have been more intensive in other areas of the catchment than recorded in the gauge.

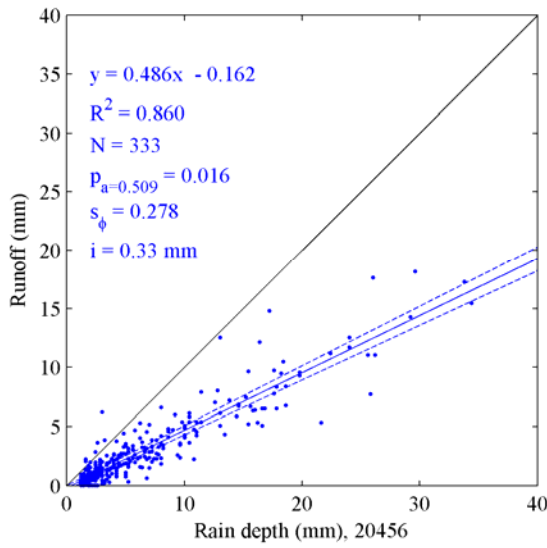


Figure C.3 Corresponding measurements of runoff and rain in gauge 20456.

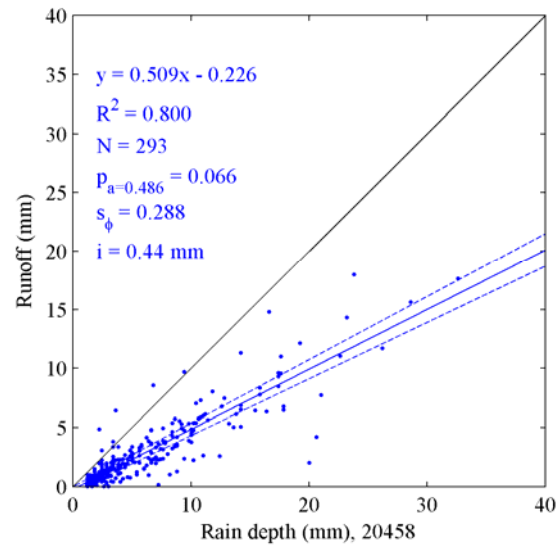


Figure C.4 Corresponding measurements of runoff and rain in gauge 20458.

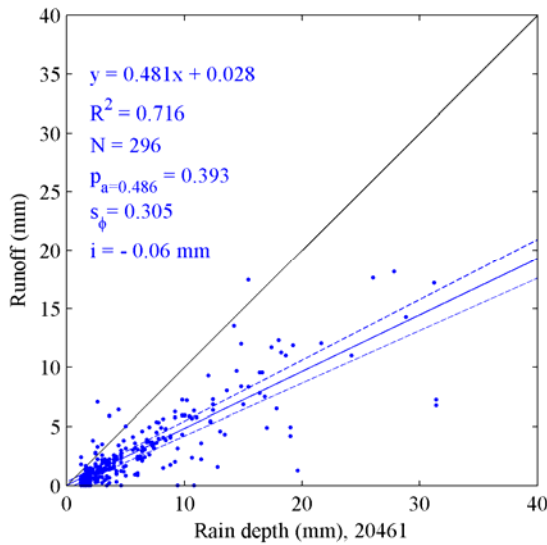


Figure C.5 Corresponding measurements of runoff and rain in gauge 20461.

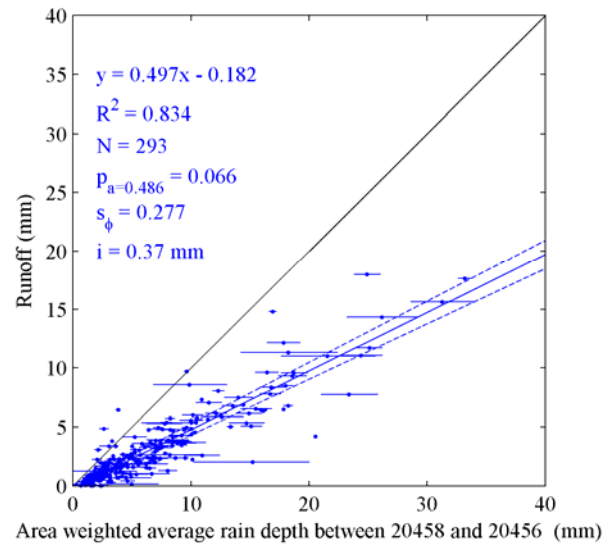


Figure C.6 Corresponding measurements of runoff and an area weighted average of 20456 and 20458.

In order to investigate if the dispersion is reduced by applying both rain gauges in Frejlev (20456 and 20458), an area weighted average of the rainfall depths are presented in Figure C.6. The end points of the horizontal lines of the figure indicate the rainfall depths measured in the individual rain gauges, and it is obvious that the dispersion between the gauges is quite large for some events. No improvement of the standard deviation nor the correlation coefficient is observed by doing the weighted average, and the hydrological reduction factor corresponds somewhat to of mean of the two individuals. With the purpose of investigating if the dispersion might be reduced by separating the rainfall data in events with

large and small deviation between the gauges, Figure C.7 is presented. Separating between events in which the rain depth deviation between the gauges is higher and lower than 50 % respectively, does not change the slope of the regression lines (the hydrological reduction factor). However the confidence interval of the events with more than 50 % deviation is much wider. This is however primarily due to difference in the number of events in the two groups, and it is not possible to conclude that a smaller dispersion is present in events in which the deviation between the gauges are small, nor the opposite. A deviation of more than 100 % was also investigated, but too few events fulfilled this criterion.

The soil saturation and the infiltration capacity of the catchment are neglected using the Time-Area method. To test this hydrological simplification the events are divided in groups with dry weather periods before an event corresponding to more and less than 24 hours respectively. The hypothesis is that events with a large dry weather period before rain start have a lower reduction factor and a larger initial loss due to a larger infiltration capacity of the soil. On the contrary, if the soil is saturated, a large reduction factor and small initial loss is expected. This is to some extend also found in Figure C.8, though the difference in the hydrological reduction factor is just on the limit of being significant. The quite small deviation between the two reduction factors is probably due to the fact that a very little part of the runoff actually originates from semi-pervious or pervious surfaces. As the infiltration capacity is assumed to depend very little on the dry weather period on the impervious surfaces cf. the definition of impervious, it is not possible, using the Frejlev data, to reject the Time-Area method on this account, due to very little differences between the reduction factor in the two situations. Nor is it possible to accentuate the Horton infiltration method over the Time-Area method.

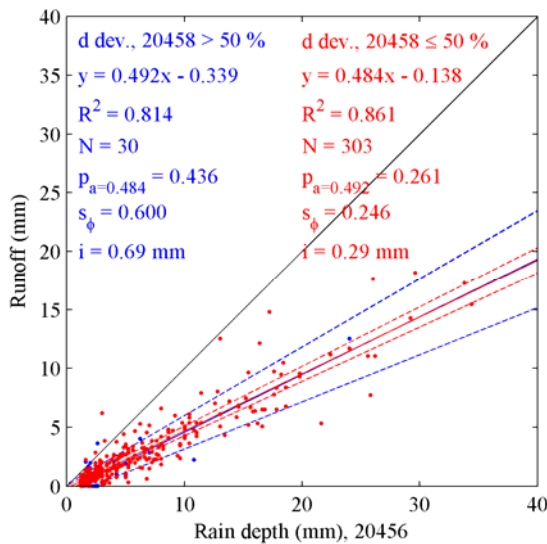


Figure C.7 Corresponding measurements of runoff and rain in gauge 20456 with separation between events with rain depth deviation lower and higher than 50 %.

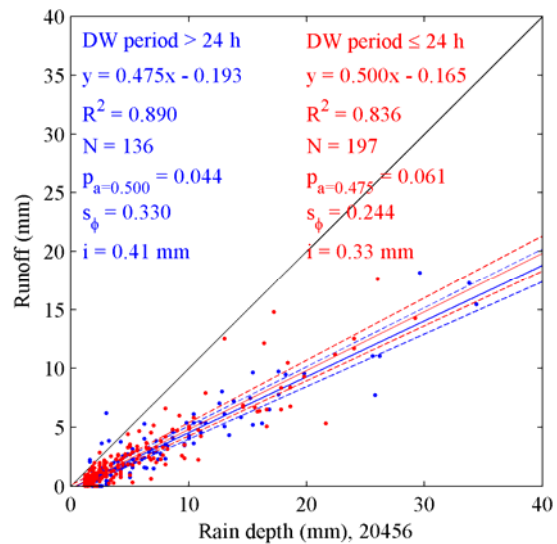


Figure C.8 Corresponding measurements of runoff and rain in gauge 20456 with separation between events with dry weather (DW) period lower and higher than 24 hours before the rain starts.

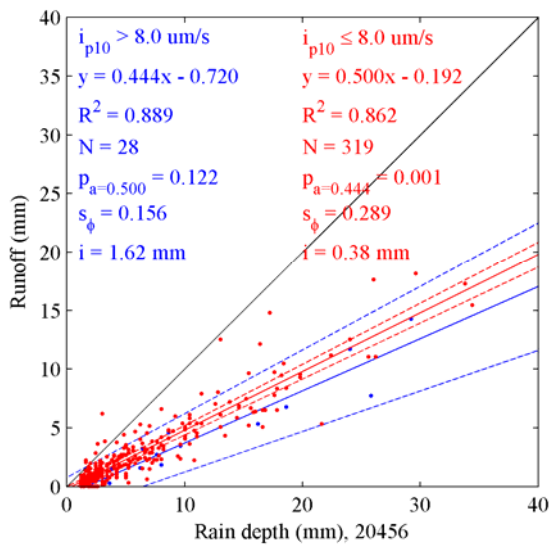


Figure C.9 Corresponding measurements of runoff and rain in gauge 20456 with separation between events with high rainfall intensities ( $>8 \mu\text{m/s}$ ) and low rainfall intensities ( $\leq 8 \mu\text{m/s}$ )

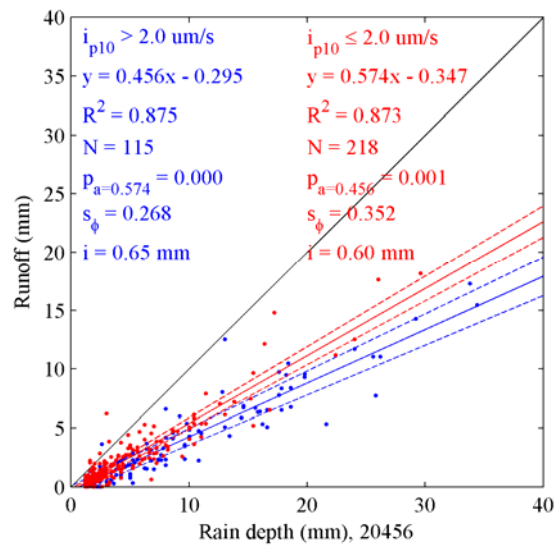


Figure C.10 Corresponding measurements of runoff and rain in gauge 20456 with separation between events with high rainfall intensities ( $>2 \mu\text{m/s}$ ) and low rainfall intensities ( $\leq 2 \mu\text{m/s}$ )

To test how the hydrological reduction factor depends on the rainfall intensity a separation between events with a 10 minute peak intensity larger and smaller than  $8 \mu\text{m/s}$  is presented in Figure C.9. According to the Danish design rain the 10 minute aggregation level with a return period of 0.5 years corresponds to  $8 \mu\text{m/s}$  (Linde et al. 2002). It is expected that events with intensities larger than  $8 \mu\text{m/s}$  have a larger runoff than events with lower intensities. This is however not significant. The result might be due to a regression line for the high peak intensities based on very few observations ( $N=28$ ). However, if the observed high peak intensities are very spatially local which causes the rain to be non-homogeneously distributed over the catchment a smaller reduction factor would be expected. In order to test if the tendency is the same for events with smaller return periods a lower threshold of  $2 \mu\text{m/s}$  is empirically chosen and presented in Figure C.10. The results show a significantly lower reduction factor for the high intensive events which is quite surprising. It is interpreted as an indicator of the fact the spatial rainfall variability is larger for high intensive events than for events with lower intensities. The phenomenon was also tested using different aggregation levels with larger averaging periods than 10 minutes, but the results did not differ from the presented.

Another way to investigate the spatial rainfall variability is by comparing the peak intensities observed in two gauges. In Figure C.11 the deviations between the peak intensities are used to separate events in groups with deviation larger and smaller than 50 % respectively. Results show a large probability (however not significant) that events with peak intensity deviations larger than 50 % have a smaller regression line slope, which supports the hypothesis that high intensive rainfall events are spatially local and therefore not distributed equally over the catchment. It is therefore evident that implementing an urban drainage

model based on only one rain gauge and using an average reduction factor will overestimate the total runoff for high intensive events. However locally in the drainage system these high intensive events might cause surcharge or flooding, which can be very difficult to predict using a global reduction factor and a uniformly distributed rain.

Arnbjerg-Nielsen and Harremoes (1996a) suggested that the hydrological reduction factor might be larger for extreme events (defined as events with a rain depth larger than 10 mm). This hypothesis is tested in Figure C.12. No such relationship could be proven using the Frejlev data as the regression lines are not significantly different. However, the 95 % confidence intervals are quite wider using the events with rain depths larger than 10 mm, so there a possibility that the statement might be true. Nevertheless, it would be more reasonable to define extreme events according to peak intensities as presented above instead of rainfall depth.

## C.5 Conclusion

In theory, the hydrological reduction factor corresponds to the part of the areas that contribute to the runoff. However, in this appendix the reduction factor is used as a ratio measure between the rainfall depth and the runoff from these surfaces. By fixing the impervious areas, knowing that this in some cases might be wrong, it is possible using the reduction factor to compare the observed rain and runoff using a single value. Accepting the uncertainty by assuming uniform distributed rain over the whole catchment, the variance of the reduction factor is used as a measure of the spatial rainfall variability per event.

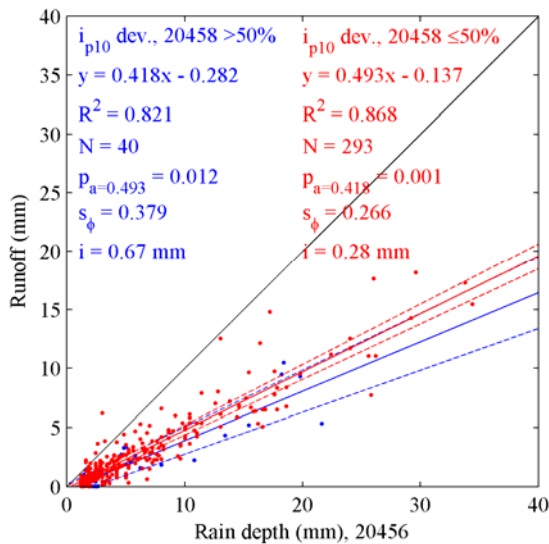


Figure C.11 Corresponding measurements of runoff and rain in gauge 20456 with separation between events in which the 10 minute peak intensities deviate more and the less than 50 % between gauge 20456 and 20458

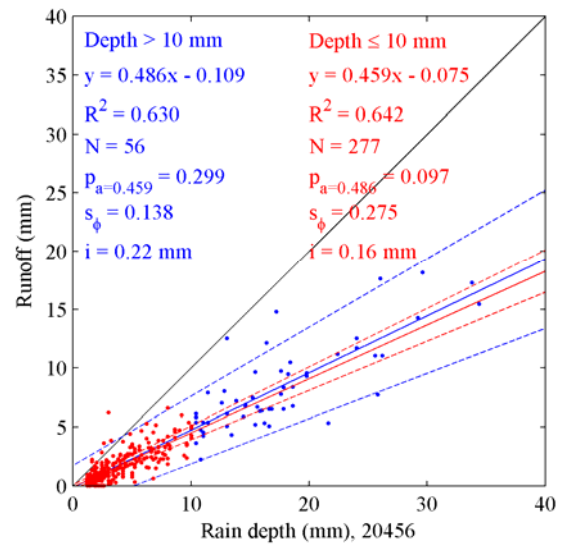


Figure C.12 Corresponding measurements of runoff and rain in gauge 20456 with separation between events with a total ran depth smaller and larger than 10 mm.

The hydrological reduction factor is calculated using data from three different rain gauges. Small deviations in the average reduction factor are observed, but these are not significantly different statistically. However quite a large dispersion around the average reduction factor is observed, and a larger dispersion is observed using rainfall data from the gauge with the greatest distance from the catchment, compared to the data from the gauges situated within the catchment.

Basic hydrological theory states that the hydrological reduction factor and initial loss should depend on the soil saturation i.e. the dry weather time before an event. This could however not be observed analyzing the Frejlev data - most like due to a very little runoff contribution from semi-pervious and pervious surfaces. This result is used to discard the complex Horton infiltration model in favor of the simpler Time-Area model as choice for the hydrological part of the surface runoff model.

Another hypothesis is that the runoff might be relatively larger for extreme events (high intensive events), as the rainfall intensity will exceed the infiltration capacity on the semi-pervious and pervious surfaces and generate runoff. Using the event peak intensities to divide events into groups of low and high intensities, show that the reduction factor assumes lower values for the high intensive events. This obviously conflicts the basic hydrological theory, but comparing the intensities recorded in two rain gauges shows that the difference between high intensities for the same events are quite large, which indicates a small spatial distribution of these high intensive events. For the high intensive events the rainfall recorded in only one gauge is therefore not representative for the whole catchment, which is why the reduction factor assumes lower values.

I would however be interesting to investigate if a larger runoff might be observed if a perfect rainfall input was available, e.g. using high spatial resolution radar data. This would most likely also reduce the dispersion of the regression line, corresponding to a smaller standard deviation of the hydrological reduction factor.

Regardless of the rainfall input a mean reduction factor of  $\varphi = 0.49$  and a standard deviation of  $s_\varphi = 0.28$  can be used in the Frejlev case. Doing stochastic urban drainage modeling the reduction factor can be sampled from a positively truncated normal distribution with these two parameters. The observed standard deviation of the reduction factor is quite large due to the uncertainty of spatial rainfall extent. Prediction of runoff using urban drainage models is therefore highly uncertain, when rainfall measurements from a single rain gauge is applied as model input and the standard deviation of the reduction factor is used to compensate for the insufficient rainfall input. It is however possible, doing Monte Carlo simulations, to match the observed runoff volumes by the model, but uncertainty on the prediction of water levels is still present.



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# Paper I

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## Assessment of runoff contributing catchment areas in rainfall runoff modelling

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# Assessment of runoff contributing catchment areas in rainfall runoff modelling

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**Abstract** In numerical modelling of rainfall caused runoff in urban sewer systems an essential parameter is the hydrological reduction factor which defines the percentage of the impervious area contributing to the surface flow towards the sewer. As the hydrological processes during a rainfall are difficult to determine with significant precision the hydrological reduction factor is implemented to account all hydrological losses except the initial loss. This paper presents an inconsistency between calculations of the hydrological reduction factor, based on measurements of rainfall and runoff, and till now recommended literature values for residential areas. It is proven by comparing rainfall-runoff measurements from four different residential catchments that the literature values of the hydrological reduction factor are over-estimated for this type of catchment. In addition, different catchment descriptions are presented in order to investigate how the hydrological reduction factor depends on the level of detail regarding the catchment description. When applying a total survey of the catchment area, including all possible impervious surfaces, a hydrological reduction factor of approximately 0.5 for residential areas with mainly detached houses is recommended – contrary to the literature recommended values of 0.7–0.9.

**Keywords** Catchment area assessment; hydrological reduction factor; initial loss; rainfall measurements; urban runoff modelling

## Introduction

Hindcast analysis and extreme event statistics are used more and more frequently to analyze the efficiency of urban storm water systems including determination of combined sewer overflow volumes and flooding of critical levels, e.g. in basements or road surfaces. When such analyses are based on simulations performed by rainfall runoff models, one of the essential parameters is the quantification of the surface runoff. The fraction of rainfall event volumes (rainfall depth) running off from roads, pavements, roofs, car entrances, etc. to an urban sewer system is controlled by numerous surface factors such as evaporation, surface permeability, surface texture, surface slope, the whereabouts of gullies, etc. In general, these factors are often difficult to quantify with high precision, resulting in an uncertain determination of runoff volumes. However, sewer flow and rainfall depth measurements can improve the estimation of runoff volumes by comparing the runoff volume to the corresponding rainfall depth (volume) in a number of rainfall events. Relating measured runoff volumes solely to the impervious part of the catchment area, the quantity of runoff (runoff depth) can be estimated. Furthermore, such runoff depths will frequently relate linearly to the rainfall depths, allowing for a definition of the hydrological reduction factor and the rainfall initial loss as the slope and the rainfall depth cut-off value of this linear relation.

This paper will present results from previous studies of the relationship between rainfall and runoff and compare these results to default values of the hydrological reduction factor and initial loss from relevant technical literature. The second part of the paper will

investigate, based on measurements of rain and runoff from a flow monitoring station in the town of Frejlev (Schaarup-Jensen *et al.*, 1998), how the runoff depth quantification depends on the assessment of impervious areas. Using Geographical Information Systems (GIS), four different scenarios are presented in order to investigate how the hydrological reduction factor and initial loss depend on the extent of impervious areas in the catchment.

### Previous investigations

The hydrological reduction factor and the initial loss are essential parameters when modelling urban storm water runoff, e.g. in the sewer modelling system MOUSE (Lindberg and Willemoes Joergensen, 1986). But often it can be difficult to quantify these parameters for a specific catchment, due to a lack of necessary calibration and validation data. Therefore practising engineers often have to rely on default values found in relevant technical literature, and trust that simulated runoff volumes represent the actual volumes of water. In Table 1 some recommended values are exemplified.

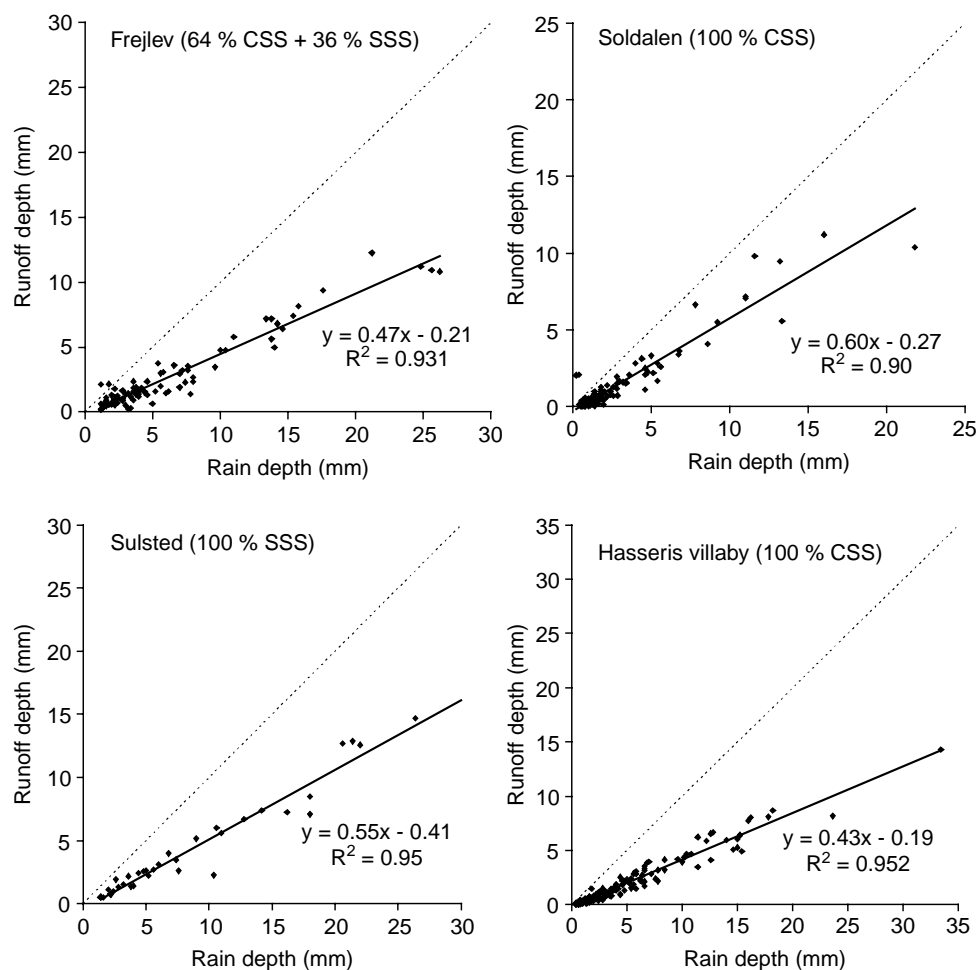
In Denmark several investigations within the national plan for the Aquatic Environment have been conducted in order to determine the environmental impacts of combined sewer overflows (CSOs). In these investigations corresponding rainfall and flow measurements in urban sewer systems have been performed partly aiming at quantifying the hydrological reduction factor and initial loss for a number of catchments (Miljoestyrelsen, 1997; Miljoestyrelsen, 1990; Nordjyllands Amt, 2004; Arnbjerg-Nielsen and Harremoes, 1996). Figure 1 presents selected results from the investigations at four different Danish sites—all residential areas mainly with detached houses. Frejlev, Sulsted and Hasseris Villaby are situated in the northern part of Jutland whereas Soldalen is situated north of Copenhagen. Facts about the four catchments are listed in Table 2 together with the calculated values of the hydrological reduction factor and the initial loss.

In Figure 1 the regression line slope represents the hydrological reduction factor and the intersection with the rain depth axis represents the initial loss. The impervious area is for all four catchments assessed, with a total survey of all impervious and semi-impervious surfaces including roads, pavements, all roof surfaces, car entrances, etc. Some researchers and practising engineers prefer to not to use the impervious percentage and the hydrological reduction factor, but instead the product of the two, labelled the runoff coefficient, therefore this value is also presented in Table 2.

Comparing Tables 1 and 2 leads to the conclusion that recommended Danish literary values of the reduction factor are larger than those calculated for the four catchments. In the worst case it is evident that the literary value is up to almost 100% larger than the calculated values. In runoff calculations, a practice based on the recommended values of Table 1 could cause almost twice as large a model runoff volume as in reality. This indicates that either the literary values are assessed too large or that the area of impervious surfaces contributing to the urban runoff in residential areas is smaller than accounted for.

**Table 1** Danish literature values of the hydrological reduction factor and initial loss

Reference	Hydrological reduction factor (–)	Initial loss (mm)
Miljoestyrelsen, 1990	0.7–0.9	0.5–1.0
DHI, 2003	0.9	0.6
Linde <i>et al.</i> , 2002	0.7–0.8	0.5–1.0
Jensen, 1990	0.61–0.84	0.48–0.92
Arnbjerg-Nielsen and Harremoes, 1996	0.73	0.5



**Figure 1** Corresponding measurements of rainfall and runoff from four different Danish residential urban catchments. Frejlev data is based on a catchment description by the Consulting Engineers and Planners, NIRAS (NIRAS, 1995). Soldalen data is adapted from Miljøstyrelsen (1997). Sulsted data is adapted from Nordjyllands Amt (2004). Hasseris Villaby data is adapted from Miljøstyrelsen (1997)

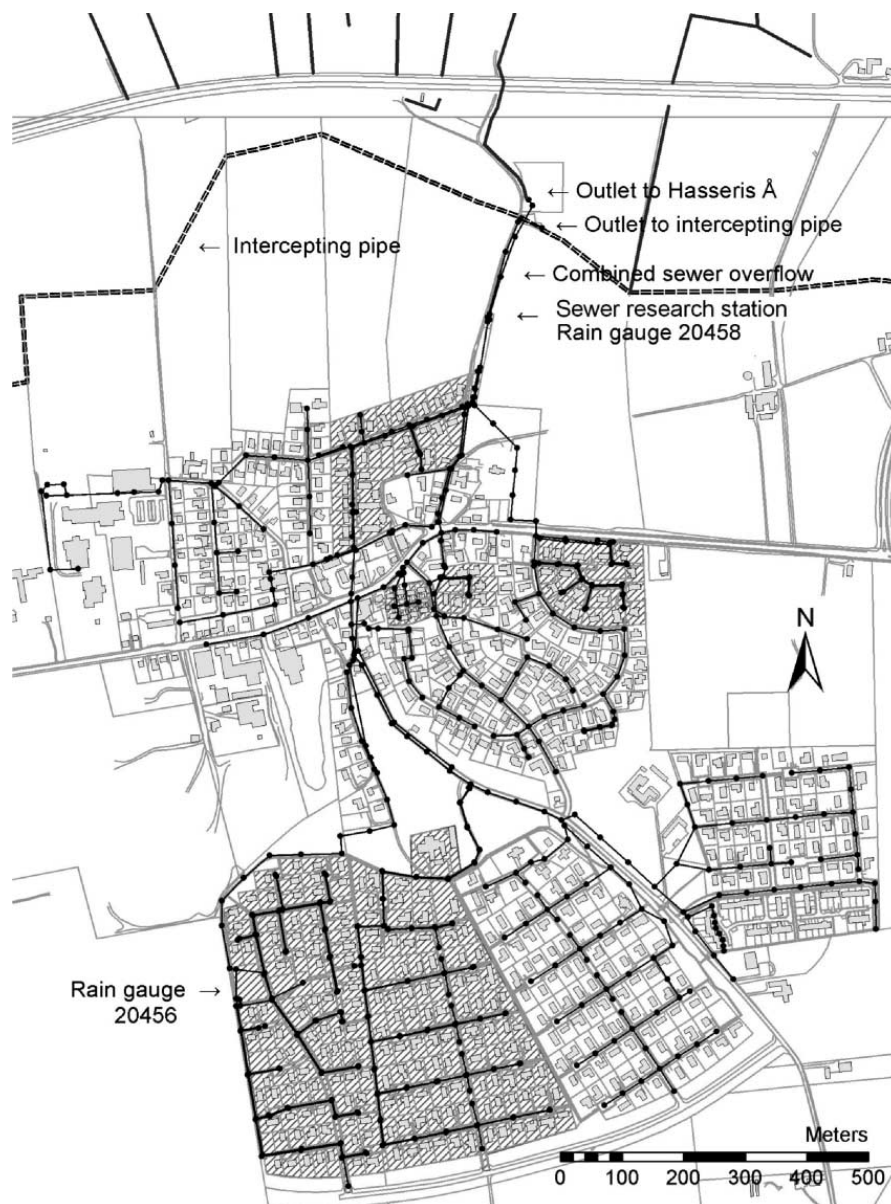
In the next section a very detailed survey on catchment, Frejlev, is carried out, trying to uncover how the impervious area of this catchment must be determined and how the reduction factor and catchment assessment depend on each other.

### The Frejlev catchment

Since 1997, Aalborg University has operated a research and monitoring station in the small town Frejlev, cf. Figure 2, where continuous sewer flow measurements are sampled

**Table 2** Facts about the four sites, and the calculated values of the hydrological reduction factor and the initial loss. CSS: combined sewer system; SSS: separate sewer system

Catchment	Frejlev	Soldalen	Sulsted	Hasseris villaby
Type of catchment	CSS/SSS	CSS	SSS	CSS
Total catchment area (ha)	79.7	10.2	14.9	94.0
Impervious area (ha)	30.9	3.2	4.8	31.0
Impervious area (%)	38.8	30.9	32.3	33.0
Measuring period	1998–2001	1992–1994	2002–2003	1994–1995
Number of rain events	96	108	33	162
Hydrological reduction factor (-)	0.47	0.60	0.55	0.43
Initial loss (mm)	0.4	0.4	0.7	0.4
Runoff coefficient (%)	18.2	18.5	17.8	14.2



**Figure 2** The sewer system of Frejlev. The areas with hatching are separate sewer systems and the rest are combined systems

from a catchment of 87 ha<sup>1</sup>. During dry weather waste water is discharged to Aalborg West Waste Water Treatment Plant *via* an intercepting pipe north of Frejlev. During wet weather a combined sewer overflow (CSO) discharges some of the waste and runoff water to the small stream, HasserisÅ. The calculated number of overflows is approximately 8–10 per year. The flow is measured, every 20 s, with to electromagnetic flow meters of the Parti-Mag type manufactured by ABB Automation Products GmbH, Göttingen, Germany. The two flow meters, where the one are used for dry weather flow measurements and the other for wet weather flow measurements, can be considered very precise, with a maximum flow rate error of 1–1.5%.

The sewer system consists of a little more than 550 manholes, two weirs and three storage basins. The total catchment area is calculated to approximately 87 ha<sup>1</sup> and the

<sup>1</sup> In the new survey, conducted by the authors, the total catchment area are 10% larger than stated in Table 2.

catchment consists of 620 houses and approximately 11 ha road areas including 2 ha of pavement. The catchment mainly consists of detached houses, some terrace houses, a school and a small centre with a few shops.

#### Assessment of runoff contributing catchment areas

This section will present a catchment assessment for Frejlev, carried out specifically for this paper, in order to compare this with the catchment description completed by NIRAS (1995). To study how the hydrological reduction factor relies upon the size of the contributing catchment area, four different catchment scenarios are presented. A different catchment area for each of the four scenarios is introduced, depending upon which surfaces runoff to the sewer system is assumed to occur. The following assumptions have been made for the assessments of the catchment areas:

Scenario 1: Road surfaces including pavements, car entrances, and roof surfaces including garages, tool sheds, covered and uncovered terraces, etc.

Scenario 2: Road surfaces including pavements, and roof surfaces including garages, tool sheds, covered and uncovered terraces, etc.

Scenario 3: Road surfaces including pavements and roof surfaces.

Scenario 4: Road and roof surfaces.

Digital cadastral and technical maps from Aalborg Municipality (Aalborg Kommune, 2001) were used in the catchment assessment. Alternatively, aerial photographs could have been used, but such were not available in high resolution as to determine impervious surfaces. The results of the detailed survey for each of the four scenarios are stated in Table 3.

The catchment assessment for Frejlev (NIRAS, 1995), cf. Table 3, corresponds to scenario 1 as the same impervious areas are included. Even though a larger total and impervious area is calculated in scenario 1, compared to NIRAS (1995), the impervious percentage remains almost the same (the difference is 1.1 percentage points). The increase in the total and impervious areas are primarily due to the urban development during the almost 10 years between the two surveys.

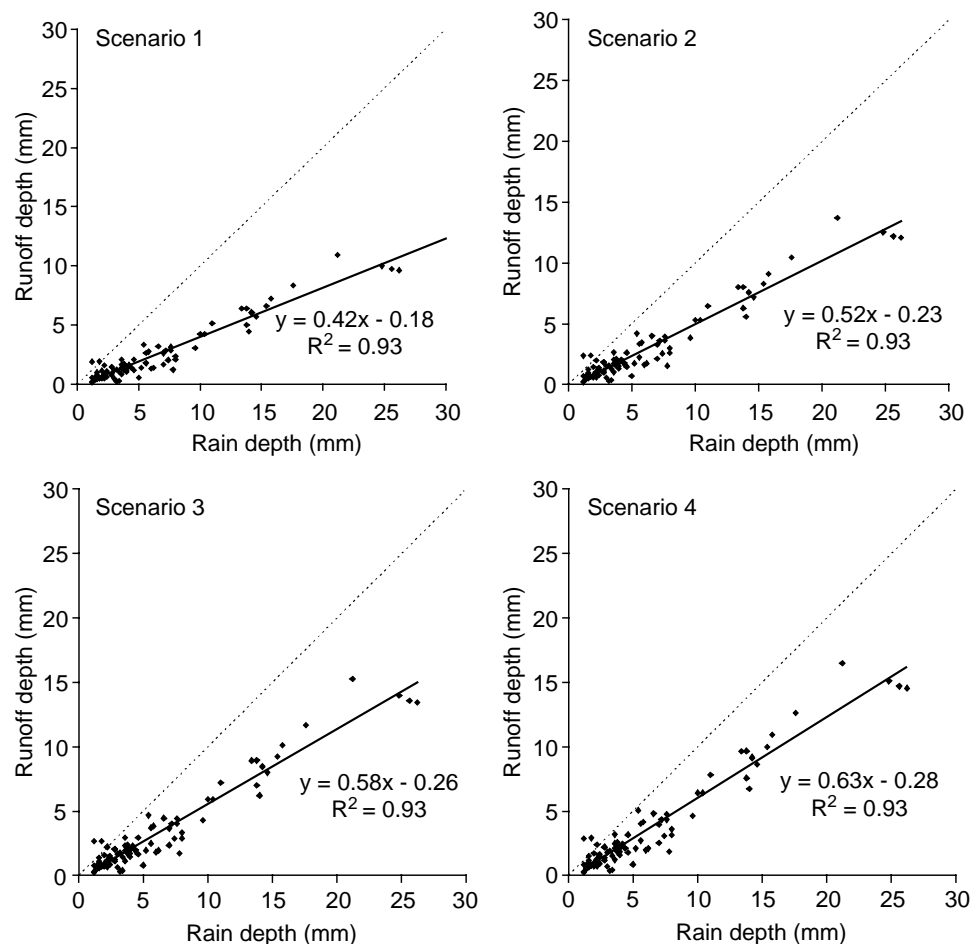
By way of comparison Miljoestyrelsen (1992) states that for residential areas with detached houses the impervious area is 20–35%, and Linde *et al.* (2002) states that for small and big cadastres the corresponding intervals are 25–30% and 20–25% respectively. Frejlev consist of a mixture of both small and big cadastres. Despite the difference in the catchment assessment the impervious percentage of the four scenarios almost fit in the intervals from the literature, even though the impervious percentage of scenario 1 is a bit larger.

#### Results

Based on the Frejlev measurements of rainfall and runoff volume, cf. Figure 1, and the calculated impervious areas, cf. Table 3, new rain-runoff charts are produced in Figure 3.

**Table 3** Calculated impervious catchment areas. The total catchment area is in the four scenarios calculated to 87.0 ha. Using the new total catchment area this results in 29 ha (33%) SSS and 58 ha (67%) CSS

	Road areas (ha)	Pavement areas (ha)	Roof areas (ha)	Car entrances (ha)	Accumulated impervious area (ha)	Impervious area (%)
NIRAS (1995)	–	–	–	–	30.9	38.8
Scenario 1	8.92	1.88	16.86	7.08	34.7	39.9
Scenario 2	8.92	1.88	16.86	0	27.7	31.8
Scenario 3	8.92	1.88	14.03	0	24.8	28.6
Scenario 4	8.92	0	14.03	0	23.0	26.4



**Figure 3** Corresponding measurements of rainfall and runoff from Frejlev with different impervious percentages used in the runoff depth calculation. The initial loss is calculated to 0.4 mm for all four scenarios

Comparing the Frejlev plot in Figure 1 with scenario 1 (Figure 3) a hydrological reduction factor of 0.47 and 0.42 respectively is shown. This difference is due to the variation in the impervious area between NIRAS (1995) and the scenario 1 survey conducted by the authors, cf. Table 3. From Figure 3 it is evident that a decrease in the impervious area with 50% (from scenario 1 to 4) results in a 40% increase of the hydrological reduction factor. Even though applying a more or less unlikely value of the impervious percentage, when only including road and roof surfaces in the impervious catchment (scenario 4), the reduction factor does not come near the recommended Danish values, cf. Table 1. It is not possible to tell whether one scenario results in a more realistic catchment description than the other, but there are indications that in residential areas the part of the impervious area contributing to sewer surface flow, is smaller than until now has been assumed in the literature. However it must be taken into consideration that the literature values, cf. Table 1, cover all types of catchments and therefore are not adapted especially to residential areas. The runoff coefficients are obviously the same (16.6%) for all scenarios, as it is the product of the impervious percentage and the hydrological reduction factor.

Schaarup-Jensen *et al.* (2005) has shown, using long term simulations in MOUSE LTS that the number of overflows to the recipient from the Frejlev sewer system will increase from 3.5 to 13.3 times per year, using a hydrological reduction factor of 0.45



and 0.90 respectively. Additionally [Schaarup-Jensen \*et al.\* \(2005\)](#) concludes using the MOUSE LTS model that the flooding frequencies and CSO volumes in Frejlev will increase considerably, when relying on the literature. This illustrates the importance of a representative value of the hydrological reduction factor in order to use simulations as a tool in sewer design.

## Conclusions

The corresponding rainfall-runoff measurements from four different Danish residential catchments with mainly detached houses, cf. [Figure 1](#), show a hydrological reduction factor in the interval of 0.42–0.60. By way of comparison the recommended values in Danish technical literature are 0.7–0.9. Hence relying on literature, will result in an overestimation of the hydrological reduction factor when using a catchment description where all possible contributions of impervious areas are included in the assessment of the impervious percentage. This conclusion is only valid for residential areas mainly with detached houses.

The detailed survey of the Frejlev catchment, concerning assessment of impervious surface areas, shows an enlargement of the hydrological reduction factor as the impervious area is reduced. Even though reducing the impervious area only to road and roof surfaces, the literary values of the hydrological reduction factor still are larger than the calculated.

In the present study it is not possible to conclude anything about the size of hydrological reduction factor in other types of catchments, e.g. residential areas with mainly blocks of flats or city centres. Likewise no conclusions can be drawn regarding to the size of the hydrological reduction factor in smaller or larger urban catchments, compared to Frejlev, as well as foreign catchments. Therefore similar investigations must be carried out in order to determine specific hydrological reduction factor for different types and sizes of a catchments. However, the authors of this paper estimate that larger catchments of the same type will show the same tendencies.

The recommended value of the hydrological reduction factor, based on the results of this paper, for Danish residential catchments with mainly detached house, is approximately 0.5, when the catchment description is based on a total survey of the catchment area, including all impervious surfaces. In this context it is important to distinguish between what the type of assignment the hydrological reduction factor is used for. In an analysis of an existing sewer system, as the one presented in this paper, a value of 0.5 is recommended for this types of catchments. But in the context of design or reconstruction of sewer systems it is possible to use the reduction factor to implement a certain safety in the calculations, e.g. an increase of 50 or 100%, to consider forthcoming extensions of the impervious area within the catchment or further attachments of catchment area to the sewer system. However, it would enhance the clarity to implement the safety factor on the impervious area instead of the hydrological reduction factor. Despite the recommendations made in this section, it is always preferable to determine the hydrological reduction factor specifically for the catchment in question using a high-quality set of measured calibration data, but unfortunately this is often not possible.

## Acknowledgements

The authors are greatly indebted to the Municipalities of Aalborg for making the Frejlev catchments and sewer system data available for this investigation, and to the County of North Jutland for runoff data from the Sulsted catchment.



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## Paper II

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### Uncertainties Related to Extreme Event Statistics of Sewer System Surge and Overflow

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## Uncertainties related to extreme event statistics of sewer system surcharge and overflow

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### ABSTRACT

Today it is common practice - in the major part of Europe - to base design of sewer systems in urban areas on recommended minimum values of flooding frequencies related to either pipe top level, basement level in buildings or level of road surfaces. Thus storm water runoff in sewer systems is only proceeding in an acceptable manner, if flooding of these levels is having an average return period bigger than a predefined value. This practice is also often used in functional analysis of existing sewer systems.

Whether a sewer system can fulfil recommended flooding frequencies or not, can only be verified by performing long term simulations - using a sewer flow simulation model - and draw up extreme event statistics from the model simulations. In this context it is important to realize that uncertainties related to the input parameters of rainfall runoff models will give rise to uncertainties related to the corresponding extreme event statistics.

This paper illustrates this problem in a case study with two different values of one input parameter - the hydrological reduction factor - in two otherwise identical operations of the MOUSE LTS model. The use of a long historical rainfall time series makes it possible to draw up extreme event statistics covering return periods of as much as 33 years. By comparing these two different extreme event statistics it is evident that these to a great extent depend on the uncertainties related to the input parameters of the rainfall runoff model.

### KEYWORDS

Hydrological reduction factor; initial loss; urban runoff modelling; MOUSE LTS; extreme event statistics; combined sewer overflow; flooding.

### INTRODUCTION

Today, assessment of the efficiency of urban sewer systems can be accomplished by performing long term simulations based on 1) historical rainfall time series, 2) a precise catchment description and 3) a well calibrated and well documented runoff model as e.g. the MOUSE LTS model (Jakobsen *et al.*, 2001). Thus the assessment can be performed based on extreme event statistics of combined sewer overflows together with extreme event statistics of flooding of critical levels, e.g. the basement level in buildings or road surfaces.

Concerning the flooding frequencies recommended design values for small schemes are listed in table 1, taken from European Standard for Drain and Sewer Systems Outside Buildings, European Standard no.: EN 752-4 (1997). The same standard states: "For larger schemes,

*design should be undertaken to limit frequency of surcharge using a sewer flow simulation model, following which the design should be checked to ensure that an adequate level against flooding will be provided at specific sensitive locations”.*

**Table 1.** Recommended design frequencies. From European Standard for Drain and Sewer Systems Outside Buildings, European Standard no.: EN 752-4 (1997).

Design storm frequency* 1 in n years	Location	Design flooding frequency 1 in n years
1 in 1	Rural areas	1 in 10
1 in 2	Residential areas	1 in 20
	City centres/industrial/commercial areas	
1 in 2	- with flooding check	1 in 30
1 in 5	- without flooding check	-
1 in 10	Underground railway/underpasses	1 in 50

\* For these design storms, no surcharge shall occur

However, existing frequency requirements from any relevant authorities overrule the recommendations of EN 752-4.

On this basis it is very likely that the code of practice within design of urban sewer systems - as well as analysis of existing systems - in years to come will be characterized by long term simulations based on the MOUSE LTS model or similar urban drainage models. Only by operating such models is it possible to come up with documentation on whether or not the system in question can meet the design flooding frequencies.

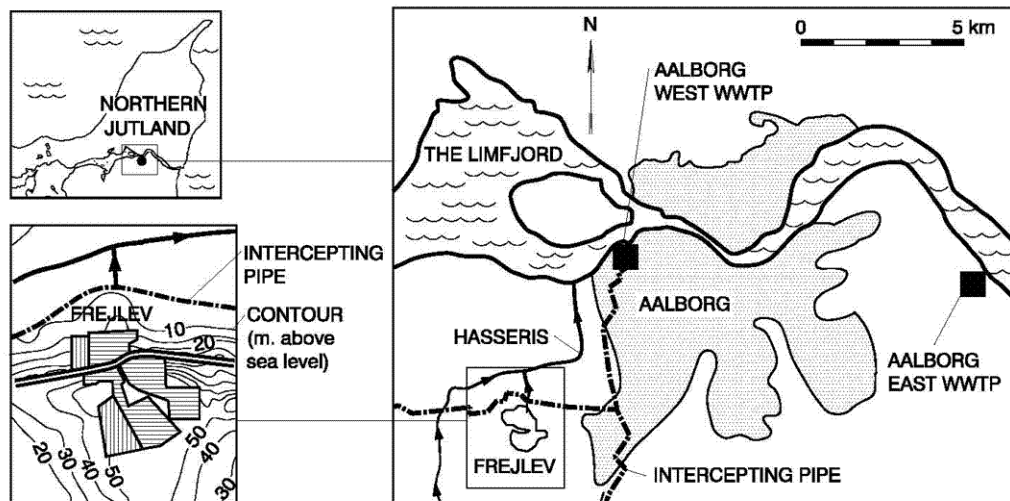
In this context it becomes very important to operate the chosen urban drainage model on a well qualified description of the catchments and – if possible – to calibrate the models regarding some important model parameters. Omitting this will lead to model simulation results, which will be characterized by a considerable uncertainty in extreme event statistics. Consequently, unreliable flooding frequencies will be the result of such model simulations.

It is the object of this paper to examine to what extent extreme event statistics from such long term simulations are influenced by an uncertain estimate of catchment parameters. In order to simplify this problem only one single parameter, the hydrological reduction factor, has been chosen for this purpose. This reduction factor has been introduced in urban drainage modeling in order to fix an appropriate estimate of the impervious area of the catchment contributing to the sewer surface runoff.

## THE TEST SITE

In 1997 a research and monitoring station was established as part of the intercepting sewer in Frejlev, a small town of 2000 inhabitants 7 kilometers southwest of Aalborg, Denmark (Schaarup-Jensen *et al.*, 1998) – cf. fig. 1 and fig. 2.

During dry weather conditions waste water flow from Frejlev is diverted into an intercepting pipe through a combined sewer overflow (CSO) structure located downhill approximately 500 meters north of Frejlev. During wet weather conditions CSOs are discharged into Hasseris, a stream which flows into the Limfjord about 6 kilometers north-east of Frejlev.



**Figure 1.** Aalborg, the town of Frejlev, the Hasseris stream and the Aalborg West waste water treatment plant (WWTP). Horizontal shading: combined sewered catchments; vertical shading: separate sewered catchments.

According to Thorndahl *et al.* (2005), the total Frejlev catchment covers an area of approximately 87 ha, situated on a hillside facing north from an uphill level approximately 55 m above sea level to a downhill level 15 m above sea level. 67% of the catchment, 58 ha, has combined sewers and the remaining 33%, 29 ha, are separately sewered, fig. 1 and fig. 2. The impervious part of the catchment is 40% corresponding to 35 ha.

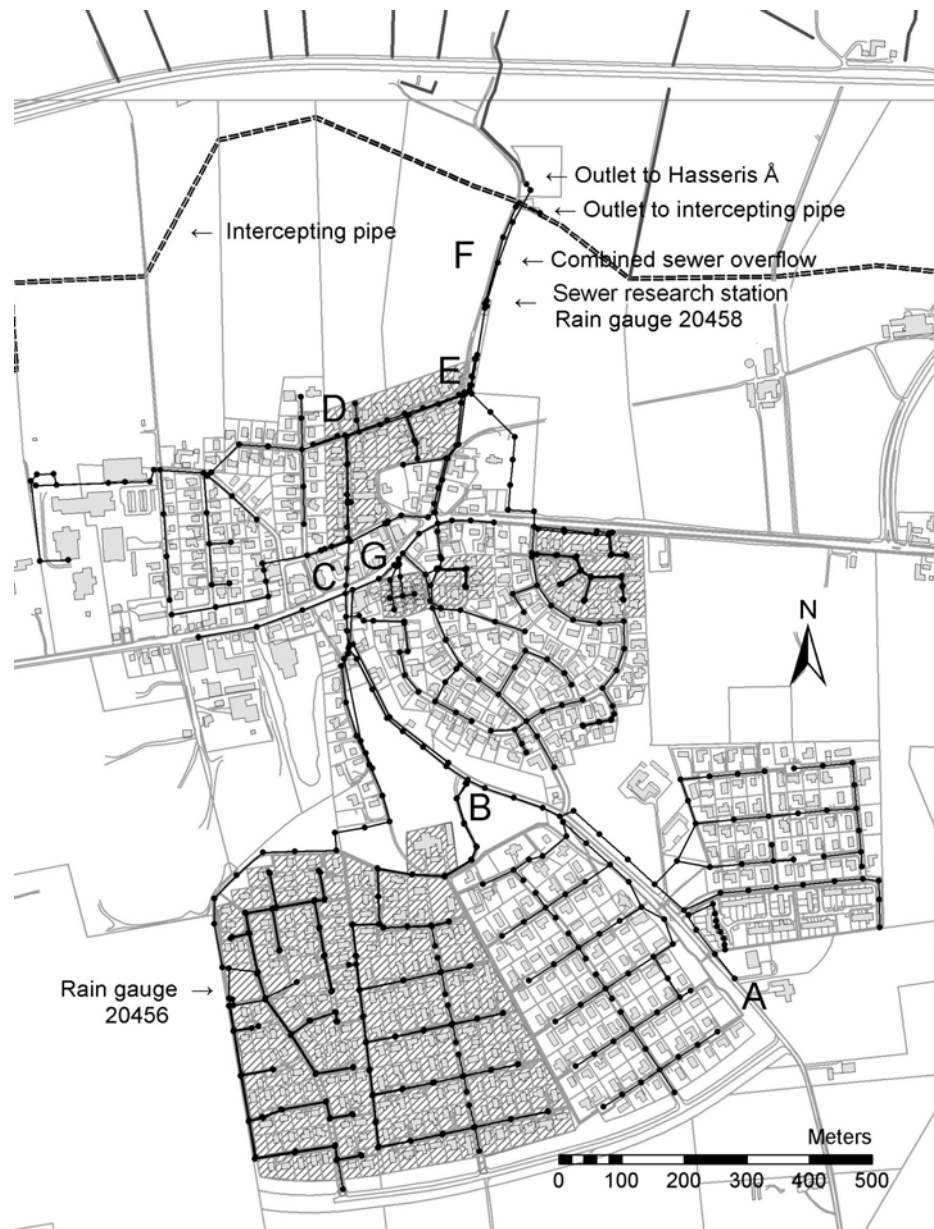
The research and monitoring station in Frejlev is located upstream and close to the CSO structure where continuous high quality time series of both dry and wet weather flow are measured in order to gain general long term knowledge of the characteristics of both flow types. Upstream from the station, the sewer pipe system is divided into two: a 300 mm diameter “dry weather pipe” and a 1000 mm diameter “wet weather pipe”. Within the station both of these pipes are equipped with high quality electromagnetic flow meters of the Parti-Mag type manufactured by ABB Automation Products GmbH, Göttingen, Germany. According to the specifications of the manufacturer, both of these flow meters function with a maximum flow rate error of 1-1.5% . The flow is measured every 20 seconds.

The flow measurements are supplemented by two automatic rain gauge stations which are included in the Danish national rain gauge system managed by the Danish Waste Water Control Committee and operated by the Danish Meteorological Institute (2004). One of the rain gauges (gauge no. 20458) is placed on top of the research station, 15 m above sea level. The second one (gauge no. 20456) is placed uphill, 55 m above sea level, in the south-western part of the town at a distance of approx. 1.2 kilometer from gauge no. 20458 – cf. fig. 2.

Until now, measurements from this station have been subject to various investigations (Schlütter and Schaarup-Jensen, 1997; Vollertsen and Hvitved-Jacobsen, 2003; Schaarup-Jensen and Rasmussen, 2004).

Measurements of precipitation and the corresponding storm water runoff flow in an urban catchment naturally results in a comparison of corresponding rainfall event volumes and

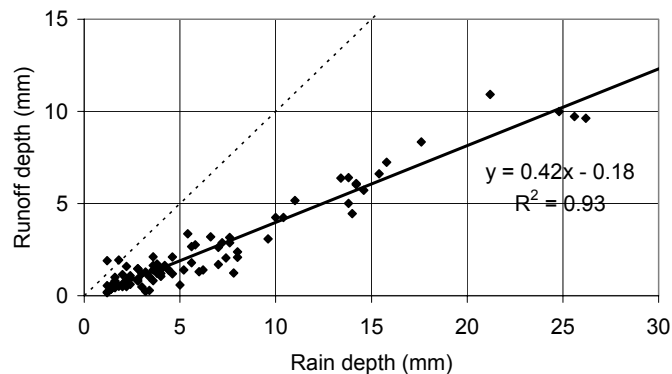
storm water runoff volumes. Relating these volumes to the impervious area of the catchment, this analysis becomes a comparison of depths – cf. fig. 3.



**Figure 2.** The town of Frejlev, the rain gauges, the sewer system, the research station, the CSO structure and the outlets to the intercepting pipe and the Hasseris stream. Areas without shading: combined sewered catchments; areas with shading: separate sewered catchments.

From figure 3 it is evident that the classical linear relationship between these two parameters seems to be present. The slope of the regression-line in fig. 3 represents the hydrological reduction factor and the intersection of the same line with the rain depth axis represents the initial loss. The initial loss – in this case 0.4 mm – is normally considered to represent a hydrological loss due to wetting and filling of terrain depressions at the beginning of a rainfall event. Likewise, the hydrological reduction factor – or more accurately 100% minus this factor - is considered to represent a hydrological loss from impervious areas during a rainfall

event. Normally this loss is explained as the percentage of the impervious catchment area from which storm water runoff is not discharged into the inlets – gullies – of the sewer system, e.g. due to local slope conditions. In the Frejlev case this loss seems to be in the order of 58%. Accordingly, the hydrological reduction factor is estimated to 42%.



**Figure 3.** Corresponding values of rainfall event depths and runoff measured in Frejlev, 1998-2001, during 96 rainfall events. From Thorndahl *et al.* (2005).

Recent investigations (Thorndahl *et al.*, 2005) indicate that 50% seems to be a “normal” value of the hydrological reduction factor for Danish catchments in residential areas – when all possible contributions to the impervious area are included in the assessment of this area, i.e. road surfaces including pavements, car entrances and roof surfaces including garages, tool sheds, covered or uncovered terraces, etc.

However, during a number of years the code of practice in Denmark in rainfall-runoff modelling has been based on Danish literature values of 70-90% of this reduction factor regardless of the type of catchment. (Miljoestyrelsen, 1990)

## MOUSE LTS SIMULATIONS

In order to describe the influence of this single catchment parameter value on the results of a long term rainfall runoff simulation on the Frejlev catchment, two MOUSE LTS simulations have been executed – one with a 45% value, the other with a 90% value of the reduction factor. Indirectly this means a choice of the time-area surface flow model (Model A) in MOUSE.

Actually, quite a lot of rainfall runoff parameters could have been taken in as stochastic parameters defined by a specific distribution having a certain mean value and standard deviation. For reasons of clarity only the hydrological reduction factor has been chosen by the authors in order to describe how the variability of one single input parameter related to a long term rainfall runoff simulation by MOUSE LTS influences the result of such a model operation.

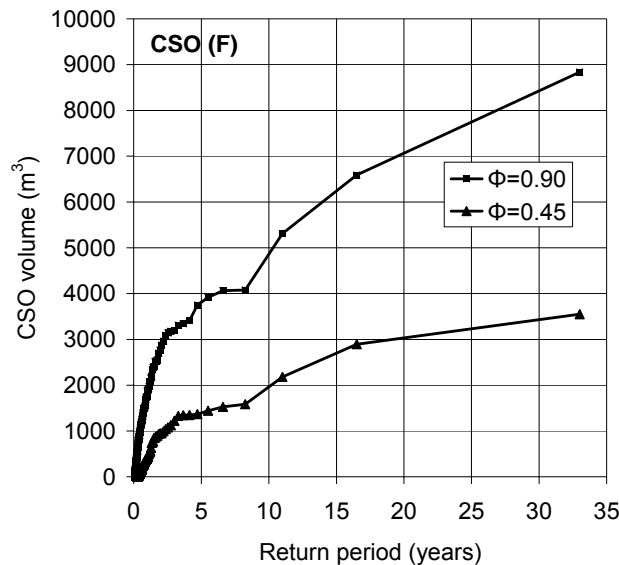
In years to come, Aalborg University will accomplish a research effort in this field in order to 1) point out the most significant input parameters to this problem 2) implement uncertainties to the extreme event statistics based on the results of such long term simulations.



The Frejlev catchment description was adapted from recent investigations performed by Thorndahl *et al.* (2005). Furthermore, an elderly historical rainfall time series – measured about the middle of the previous century in Odense, Denmark – was chosen for these simulations, simply due to the length (33 years) of this specific time series.

## RESULTS FROM SIMULATIONS

One important result from the MOUSE LTS simulations appears from figure 4 illustrating the extreme event statistics on simulated CSO volumes – see fig. 2, structure F. As expected, the difference between a simulation based on hydraulic reduction factors ( $\phi$ ) of 0.90 and 0.45 respectively is evident.

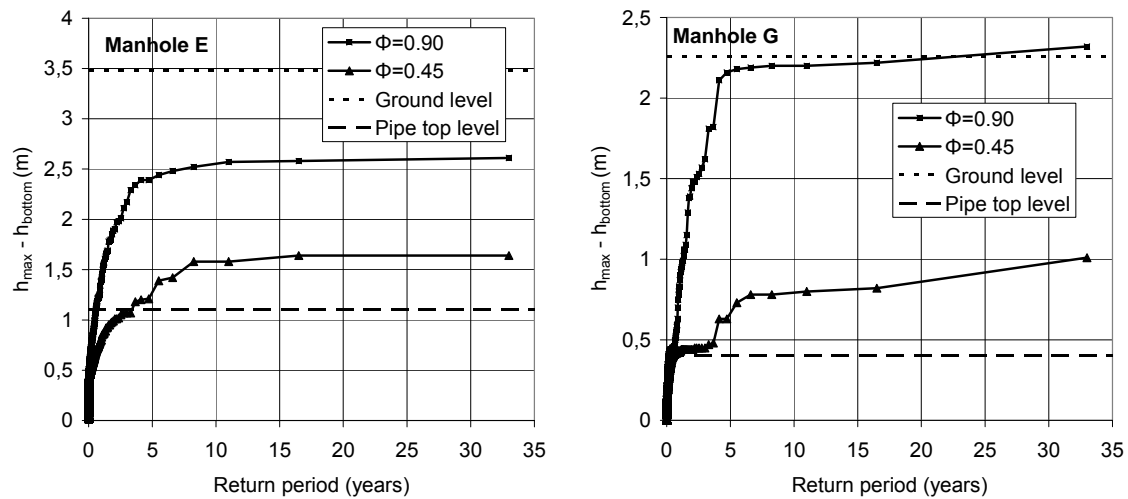


**Figure 4.** CSO volumes as a function of (average) return period.

The most extreme CSO volumes increase by a factor close to 3, from 1.500-3000 m<sup>3</sup> to 4.000-8.500 m<sup>3</sup> corresponding to average return periods between 5 and 33 years. The average volume of CSO events only increases slightly from 410 m<sup>3</sup> to 558 m<sup>3</sup> but the average number of CSO events per year increases conspicuously from 3.5 to 13.3. This difference in both extreme and average CSO numbers was expected owing to the fact that the effective drainage areas in the two MOUSE LTS simulations differ from each other by a factor of 2.

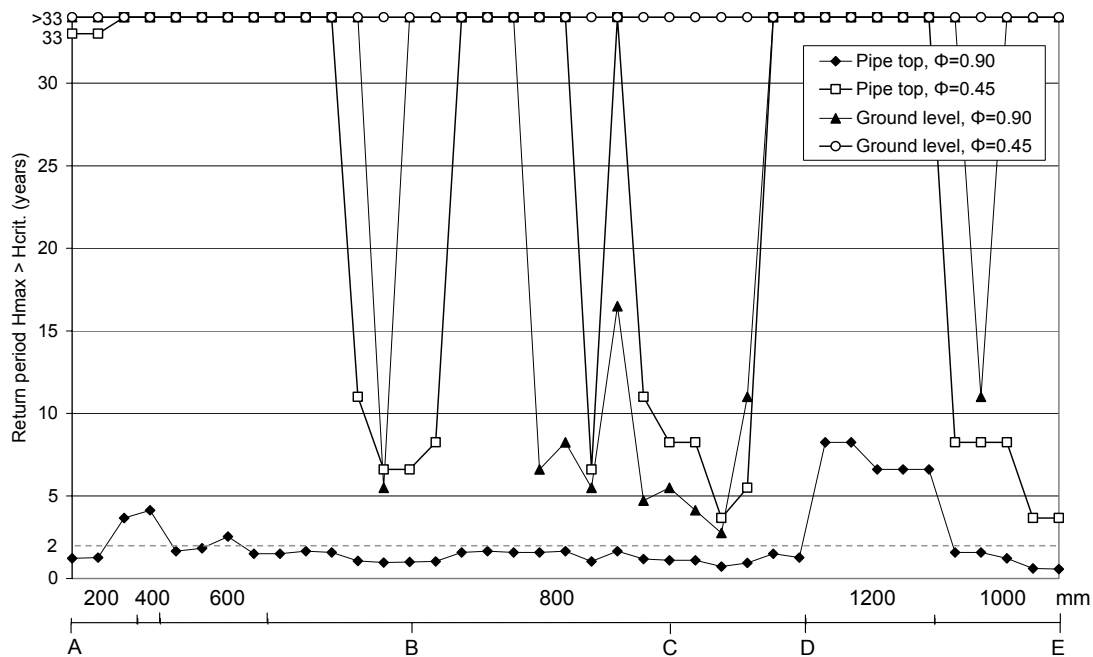
Regarding damming-up frequencies, these are illustrated in figures 5 and 6 below. Figure 5 illustrates the maximum water level,  $h_{\max}$ , during a rainfall event in two arbitrarily chosen manholes, E and G, see fig. 2. Actually the figure illustrates the distance between  $h_{\max}$  and the bottom level,  $h_{\text{bottom}}$ , of the manholes.

For manhole E it is evident that damming-up to ground level does not occur in any case. If basements can be found in the vicinity of this manhole and basement levels are defined as ground level minus 1.5-2 m, the possibility of basement flooding is very high in case of  $\phi = 0.90$  and almost negligible in case of  $\phi = 0.45$ . Furthermore, the top level of the outgoing pipe (an 1100 mm diameter pipe) from the manhole is exceeded with an average return period of less than 1 year for  $\phi = 0.90$  and approx. every 4 years for  $\phi = 0.45$ . According to table 1 this could lead to two contradictory conclusions concerning observation of the design criteria.



**Figure 5.** Flooding frequencies in the Frejlev sewer system, manhole E and G, see fig. 2.

In the case of manhole G, ground level is exceeded on average every 20 years in case of  $\phi = 0.90$  while this exceeding level never occurs in case of  $\phi = 0.45$ . The top level of the outgoing pipe (a 400 mm diameter pipe) is exceeded in both cases with return periods below 1 year.



**Figure 6.** Flooding frequencies in the Frejlev sewer system. Longitudinal profile for the stretch, A-B-C-D-E (combined sewer), see fig. 2.

Along the most significant pipe stretch in the Frejlev sewer, A-B-C-D-E (see fig. 2), the return periods of water level exceeding the pipe top level and eventually the ground level is illustrated in figure 6.

This stretch is a part of the combined sewer in Frejlev. Consequently – see table 1 – the design storm frequency was 1 in 2 years corresponding to a demand of an average return period greater than or equal to 2 years for flooding of pipe top level.

In case of  $\phi = 0.90$  the return period of flooding of pipe top level is less than 1 for a big part of this stretch. This frequency – in case of  $\phi = 0.45$  (corresponding to reality) – never becomes less than approx. 4 years. For some manholes along this stretch flooding of ground level is as frequent as every third or fourth year in case of  $\phi = 0.90$  while this in case of  $\phi = 0.45$  (in reality) happens with a frequency greater than 33 years.

## CONCLUSIONS

In this paper a plausible difference between a recommended (0.90) and a realistic value (0.45) of the hydrological reduction factor  $\phi$  for residential catchments has been presented in order to illustrate the corresponding variability in results from long term simulations.

Otherwise identical MOUSE LTS simulations based on these two different values of  $\phi$  clearly indicate, that uncertainties related to central input parameters of rainfall runoff models to a high degree are influencing extreme event statistics on results from long term simulations, e.g. CSO volumes and flooding of critical levels in the catchment such as basements and road surfaces.

Variability in estimation and/or assessment of other input variables to this type of models may have a similar influence to such extreme event statistics. Concurrently with an increasing use of long term simulations within the field of urban drainage a well organized research effort becomes a necessity in order to reveal the uncertainties related to extreme event statistics on the results from such model operations.

## ACKNOWLEDGEMENT

The authors are greatly indebted to the Municipalities of Aalborg for making the Frejlev catchments and sewer system data available for this investigation.

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## Paper III

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### Comparative Analysis of Uncertainties in Urban Surface Runoff Modelling

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# **Comparative analysis of uncertainties in urban surface runoff modelling**

Analyse comparative des incertitudes sur la modélisation du ruissellement urbain

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## **RESUME**

Le présent article fait une comparaison entre trois modèles différents de ruissellement proposés par le l'outil de modélisation numérique urbain MOUSE. En analysant l'incertitude des paramètres, on montre que les modèles sont très sensibles au choix des paramètres hydrologiques lorsqu'on compare les volumes de déversement unitaires et plus particulièrement lorsque les modèles ne sont pas étalonnés. Les cas d'inondation et de surcharge sont hautement dépendants des paramètres hydrologiques et hydrodynamiques. Aussi, l'article conclut-il que se les simulations proposées par le modèle doivent être considérées comme un outil fiable pour l'analyse des systèmes d'assainissement, des recherches plus approfondies sont nécessaires afin d'améliorer les paramètres de modélisation des ruissellements de surface.

## **ABSTRACT**

In the present paper a comparison between three different surface runoff models, in the numerical urban drainage tool MOUSE, is conducted. Analysing parameter uncertainty, it is shown that the models are very sensitive with regards to the choice of hydrological parameters, when combined overflow volumes are compared - especially when the models are uncalibrated. The occurrences of flooding and surcharge are highly dependent on both hydrological and hydrodynamic parameters. Thus, the conclusion of the paper is that if the use of model simulations is to be a reliable tool for drainage system analysis, further research in improved parameter assessment for surface runoff models is needed.

## **KEYWORDS**

Calibration, Sensitivity analysis, Surface runoff, Uncertainties, Urban drainage modelling

## 1 INTRODUCTION

In analysis and design of urban storm water drainage systems, an important tool for the consulting engineer is commercial urban drainage models such as MOUSE, InfoWorks, SWMM, etc. However, if results from these models are used in decision-making, it is all-important that the results are valid and correspond to reality. Wrong decisions, based on defective and uncalibrated model predictions, can at worst cause unrealistic estimates of flooding or combined sewer overflow frequencies, or on the other hand result in over-dimensioned - and more expensive - drainage systems with poor self-cleansing. Therefore, it is crucial to clarify where the main uncertainties in urban drainage models are located in order to either reduce the uncertainties or to take precautions in the decisions based on models results.

An urban drainage storm water model can be divided into four individual parts: the precipitation input, the hydrological surface processes, the hydrodynamics of the surface flow, and finally the hydrodynamics of the pipe flow. The object of this paper is to investigate two of the four parts, namely the hydrological surface processes and the hydrodynamics of the surface runoff, as it is the author's conviction that these part of an urban drainage model is encumbered with many and relatively serious errors. This is also described by e.g. Lei (1996), Artina et al. (2005) and Willems and Berlamont (1999).

The object of the paper is to investigate different complexities and types of both hydrological and hydrodynamic processes by comparing three different surface runoff submodels (SRM). These are compared with regards to complexity and calibration. The comparison is implemented using long term simulations and comparing results of combined sewer overflow volumes and occurrence of surcharge or flooding in the catchment. The analysis is based on setup and simulation with the MOUSE model from DHI Water & Environment, but similar models such as SWMM or InfoWorks could most certainly have been applied with the same results.

This study is carried out on the basis of the Danish Frejlev catchment where several investigations have already been completed, e.g. Schaarup-Jensen et al. (1998), Schaarup-Jensen et al. (2005), Schaarup-Jensen & Rasmussen (2004), Thorndahl et al. (2006) and Thorndahl and Willems (2006). Frejlev is a small town of approx. 2000 inhabitants, 7 km southwest of Aalborg, Denmark. The partly combined and partly separated drainage system, is equipped with two high resolution electromagnetic flow-meters (Schaarup-Jensen et al. 1998), which constantly measure the runoff from the catchment of approx. 80 hectares. Within a range of 5 km three automatic tipping-bucket rain gauges are located in and close to the town.

## 2 METHODS

For clarity reasons, it is preferable to divide the surface runoff into hydrological surface processes and hydrodynamic surface flow (or routing) processes, since the former causes zero-order errors (i.e. volume errors), and the latter causes first- and second-order errors (i.e. errors in the temporal flow variations). In addition, it is important when calibrating a model, initially to calibrate in order to minimize zero-order errors, and secondly, if possible, to calibrate to minimize first- and second-order errors.

The runoff volume from an urban catchment is calculated applying the total precipitation minus the hydrological losses such as evaporation, wetting, filling of terrain depressions and infiltration to soil. In MOUSE this calculation can be implemented using two different methods (complexities):

1. The runoff volume is calculated using a constant reduction of the precipitation on the impervious and semipervious surfaces deducted the initial loss (wetting loss and filling of terrain depressions).
2. The runoff volume is determined by calculation of the individual losses on the impervious, semipervious, and pervious surfaces, specifying wetting loss, filling of terrain depressions and infiltration rates (the latter on the semi pervious and pervious surfaces only)

The temporal flow variation on the surface is based on a calculation of the time from the precipitation hits the surface till it reaches the main drainage pipe. In MOUSE this is implemented by three different approaches (complexities):

- a. A time-area method, in which a constant concentration time on the surface is applied
- b. A kinematic wave approach, in which the velocity on the surface is calculated, depending on the water depth, by a non-linear reservoir model
- c. A linear reservoir model, in which the velocity on the surface is calculated, depending on the water depth, using a linear approach.

It is not possible, in MOUSE, to join the hydrological and hydrodynamic processes arbitrarily; therefore the hydrological approach no. 1 must be combined with the hydrodynamic approach a and c, in the following labelled the time-area model (SRM A) and the linear reservoir model (SRM C) respectively. The hydrological approach no. 2 must be combined with the hydrodynamic approach b, in the following labelled the kinematic wave model (SRM B). An example of the three different hydrographs is shown in Figure 1.

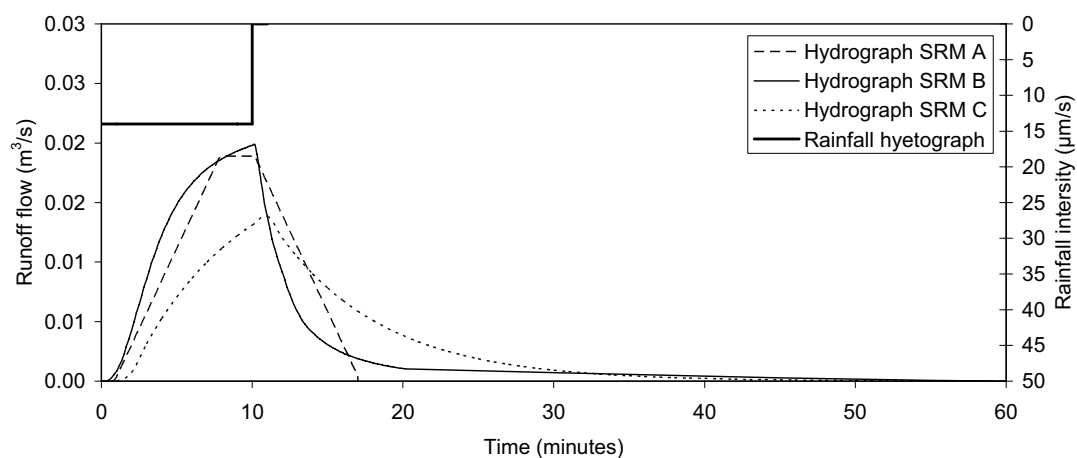


Figure 1 Hyetograph for a 10 min. uniform rainfall event with a constant intensity of 14  $\mu\text{m/s}$  and examples of hydrographs for the three different surface runoff models with default parameters.

## 2.1 Time-Area model (A)

The time-area SRM is based on the well-known time-area method which includes only the impervious and semipervious parts of the catchment in the calculation. The hydrological part of the model is controlled by two parameters; the hydrological reduction factor which defines the percentage of the impervious and semipervious area contributing to the surface flow as a result of infiltration and evaporation losses, and the initial loss (mm), which is defined as the rainfall depth loss due to wetting and filling of terrain depressions. The technical literature recommends a hydrological reduction factor of 0.7-0.9, and an initial loss of 0.5-1.0 mm. However, recent measurements from various small urban catchments in Denmark show remarkable smaller reduction factors of 0.4-0.6. (Thorndahl et al. 2006)



In the hydrodynamic SRM, a constant concentration time is assessed to every sub catchment, in order to calculate the runoff hydrograph. Assuming a rectangular sub catchment the runoff is computed proportional to the contributing area. Most often the concentration time is assessed globally, i.e. the same value for every sub catchment is used independent of the size of the sub catchment. It is difficult to specify a standard value of the concentration time as the parameter indeed depend on local conditions; however Winther et al. (2006) and DHI (2004) specify the concentration time to 5-7 minutes for small Danish urban catchments.

## 2.2 Kinematic wave model (B)

In the kinematic wave model, the catchment is divided into five different surface types - two impervious surfaces, a semipervious surface and two pervious surfaces - each defined as a percentage of the total sub catchment area. The two impervious surfaces correspond to (1) roof areas (steep areas), with no depression storage and (2) road, pavement, etc. areas (flat areas) with depression storage. From these surfaces no reduction of the rainfall volume occur (except for wetting loss and depression storage), on the contrary to the semipervious and pervious surfaces, in which the runoff volume is controlled by the infiltration to the soil. The semipervious areas cover surfaces like pavements, paved driveways, terraces, etc. and the pervious surfaces covers areas with medium and large infiltration, e.g. sandy and clayey soils. The infiltration is calculated by Hortons infiltration (Chow 1964):

$$f_{cap,i}(t) = f_{end,i} + (f_{start,i} - f_{end,i}) \cdot \exp(-a_i \cdot t) \quad (1)$$

$f_{cap,i}$  is the infiltration capacity (m/s) for one of the area types,  $f_{start,i}$  and  $f_{end,i}$  are start and end infiltrations (m/s) respectively,  $a_i$  is the Horton exponent and  $t$  is the time. This approach diverge from SRM A, by including a rainfall intensity dependency, i.e. when the rainfall intensity is larger than the infiltration capacity the runoff from the semipervious and pervious surfaces will contribute to the runoff. Kinematic wave models are often referred to as non linear reservoir in which the routing is calculated by a continuity equation: (2) and a momentum equation – in this case reduced to the Manning formulae (3) – (DHI 2004):

$$i_{eff,i} \cdot F_i - Q_i = F_i \cdot \frac{dy}{dt} \quad (2) \quad Q_i = C_{b,i} \cdot y^{\frac{5}{3}} \quad (3)$$

$i_{eff,i}$  is the effective rainfall intensity (the total precipitation deducted the hydrological losses),  $F_i$  is the catchment area,  $Q_i$  is the discharge from the catchment and  $F_i \cdot \frac{dy}{dt}$  is a storage term.  $C_{b,i} = M_i \cdot b_i \sqrt{S_t}$  and  $b_i = \frac{F_i}{L}$ .  $C_{b,i}$  is a constant,  $M_i$  is the

Manning number,  $b_i$  is the catchment width,  $S_t$  is the terrain slope, and  $L$  is the catchment length. The indices  $i$  indicate one of the five area fractions. In Table 1 an example of default values used in SRM B is shown.

Parameter	Impervious		Semipervious	Pervious	
	Steep area	Flat area	Small inf.	Medium inf.	Large inf.
Wetting (m)	$5.0 \cdot 10^{-5}$	$5.0 \cdot 10^{-5}$	$5.0 \cdot 10^{-5}$	$5.0 \cdot 10^{-5}$	$5.0 \cdot 10^{-5}$
Storage (m)	-	$6.0 \cdot 10^{-4}$	$1.0 \cdot 10^{-3}$	$1.0 \cdot 10^{-3}$	$2.0 \cdot 10^{-3}$
Start.inf. $f_{start,i}$ (m/s)	-	-	$1.0 \cdot 10^{-6}$	$1.0 \cdot 10^{-5}$	$1.0 \cdot 10^{-5}$
End.inf. $f_{end,i}$ (m/s)	-	-	$5.0 \cdot 10^{-7}$	$1.0 \cdot 10^{-6}$	$5.0 \cdot 10^{-6}$
Exponent $a_i$ ( $s^{-1}$ )	-	-	$1.5 \cdot 10^{-3}$	$1.5 \cdot 10^{-3}$	$1.5 \cdot 10^{-3}$
Manning $M_i$ ( $m^{1/3}/s$ )	80	70	30	30	12

Table 1 Default values in the kinematic wave model (DHI 2004)

### 2.3 Linear reservoir model (C)

The hydrological part of the linear reservoir model is the same as described under the time-area model (section 2.1) using the hydrological reduction factor and initial loss.

With regards to the routing, the same continuity equation (2) as in the kinematic wave approach is used. The momentum equation is linear and defined as (DHI 2004):

$$Q = C_c \cdot y \quad (4)$$

$C_c = F/T_L$ . The default value of  $T_L$  is 5 minutes (DHI 2004).

## 3 HYDROLOGICAL CALIBRATION

### 3.1 Time area model (A) and linear reservoir model (C)

The time-area model is calibrated regarding runoff volumes using corresponding measurements of rainfall and runoff from the monitoring station in Frejlev, as referred in section 1. In Figure 2 a calibration based on 8 years of corresponding rain and runoff is presented. Using a linear relationship between the rain depth and the runoff depth the two parameters in hydrological model A can be derived, when assuming a spatially uniform distribution of the rain. The hydrological reduction factor corresponds to the slope of the regression line and the initial loss to the intersection with the abscissa.

This calibration is based on a definition of the contributing area as all hard surfaces, i.e. roof and road areas, as well as pavements, paved driveways, terraces etc., corresponding to impervious and semipervious areas of 40 % of the total catchment area in Frejlev. The derived hydrological reduction factor corresponds to a runoff from these surfaces of 48 %, i.e. 19 % of the total catchment area contributes to the runoff.

### 3.2 Kinematic wave model (B)

Due to the large number of parameters in the kinematic wave model it is almost impossible to calibrate this model using measurements of rainfall and the corresponding runoff only. On the other hand it is possible to calibrate SRM B based on a calibration of SRM A. However, applying the calibration directly will lead to an overestimation of the runoff volumes as this model does not take a hydrological reduction of the impervious area, except wetting and depression storage losses into account. Thus, it is necessary to reduce the impervious areas corresponding to the hydrological reduction factor in order to get realistic runoff volumes. The most important calibration parameters are the infiltration rates on the semipervious areas, since wetting and depression losses are of minor importance and the pervious areas rarely ever contribute to the runoff except for very high intensity rainfall events. Analysing the rain-runoff data, it was expected that a rainfall intensity dependency of the runoff could be proven, and this could defend SRM B in comparison with SRM A. However, analysing 353 rainfall events a significant dependency could not be proven. Hence it is not possible to derive a threshold intensity corresponding to the infiltration capacity, in order to identify events in which the semipervious surfaces contribute to the runoff. Therefore, SRM B is calibrated against the SRM A calibration, by manually adjusting the infiltration rates on the semipervious surfaces. The calibration result regarding simulated runoff volumes in the two SRM's is shown in Figure 3. If the semipervious did not contribute to runoff, the points in Figure 3 would fit the bisector perfectly, but since some events actually contribute, as a result of the specified infiltration capacities, there is a small positive scatter.

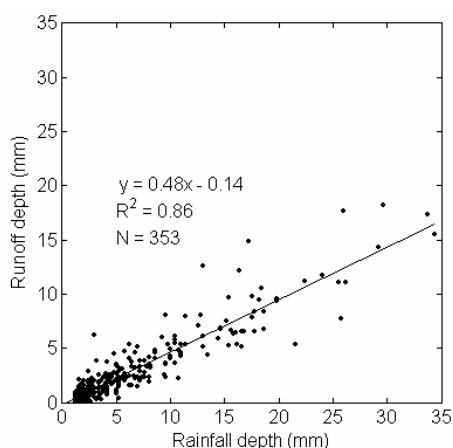


Figure 2 Calibration of the time-area model (Frejlev catchment). Hydrological reduction factor: 0.48 and initial loss: 0.3 mm.

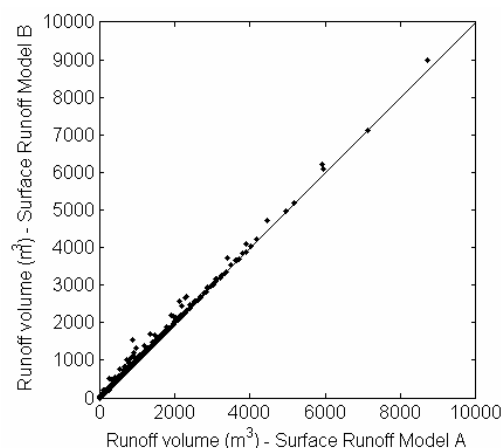


Figure 3 Results of the hydrological calibration of SRM B based on SRM A (Frejlev catchment).

## 4 SENSITIVITY ANALYSIS OF HYDRODYNAMIC PARAMETERS

Preferably a hydrodynamic calibration would be conducted as well as the hydrological calibration, but as the flow measurements available embrace the runoff from the whole catchment, the surface runoff parameters can not be isolated due to influence of hydrodynamic pipe flow parameters, e.g. friction and head loss. With regards to the missing hydrodynamic calibration, it is selected to carry out a sensitivity analysis of the hydrodynamic parameters in order to estimate in what way the parameter assessment influence the long term statistics of an urban drainage system. Seven long term simulations are completed for each of the three SRM's, using an 18.8 year rain series from the Svenstrup rain gauge, approx. 3 km from Frejlev. The results are compared with regards to overflow volumes, surcharge (i.e. full-running pipes), and flooding of the ground level. In SRM A, a concentration time ( $t_c$ ) varying from 3 to 21 minutes is selected. In SRM B the catchment length ( $L$ ) is varied from 10 to 100 m and other values are kept fixed, corresponding to the  $C_b$ -values as shown in Table 2, for a subcatchment area of 2500 m<sup>2</sup>. The sensitivity analysis of SRM C is based on a variation of the lag time ( $t_L$ ) from 1 to 18 min. corresponding to the  $C_c$ -constants shown in Table 2.

model sim. no.	A		B		C	
	$t_c$ (min)	$T_{sur}$ (years)	$C_b$ (m <sup>4/3</sup> /s)	$T_{sur}$ (years)	$C_c$ (m <sup>2</sup> /min)	$T_{sur}$ (years)
1	3	1.8	2000	2.3	2500	4.7
2	6	3.1	1000	2.3	833	18.8
3	9	6.3	667	2.3	417	18.8
4	12	6.3	500	2.3	278	>18.8
5	15	18.8	400	2.6	208	>18.8
6	18	18.8	267	3.7	167	>18.8
7	21	18.8	200	4.7	139	>18.8

Table 2 Example of the parameters used in the sensitivity analysis and modelled return periods of surcharge in the most critical manhole (distance: 1250 m cf. Figure 5)

Results of overflow simulations are shown in Figure 4 which illustrates that varying the hydrodynamic parameters in a realistic interval have little effect on the overflow volumes. For a return period of two years the mean of each of the three SRM's yields 1468, 1491, and 1474 m<sup>3</sup> respectively. The difference between the smallest and the largest volumes, for the return period of two years, is calculated to 4.1, 4.8, and 9.8 % respectively. In Figure 4 the results of one simulation in which SRM A is hydrologically uncalibrated (corresponding to a standard value of the hydrological

reduction factor of 0.9 and concentration time of 7 min) is also shown for comparison with the varied hydrodynamical parameters. It is obvious, regarding overflow volumes, that hydrological parameters are far more decisive than hydrodynamic parameters.

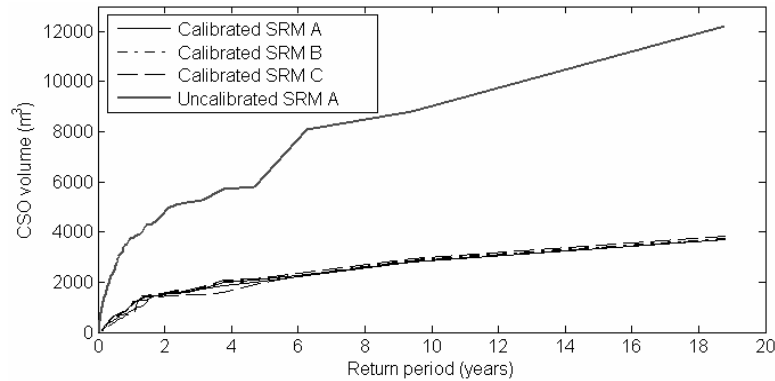


Figure 4 Long term simulations of overflow volumes from the Frejlev sewer system. For sake of clarity only the results corresponding to simulation no. 1 and 7 are shown. The gray line corresponds to the simulation with a hydrologically uncalibrated model.

It is not possible to determine any dependency between any of the SRM's and frequencies of flooding of ground level, as no flooding occurs during the 18.8 simulated years. However, the surcharge is very sensitive to variation in the hydrodynamic parameters for all three models, as illustrated on the longitudinal profile, Figure 5, and in Table 2. The return period of surcharge range from 1.8 years to 18.8 years for the most critical manhole, using model A with a concentration time of 3 and 21 minutes respectively. The same result is also verified in Thorndahl & Willems (2006).

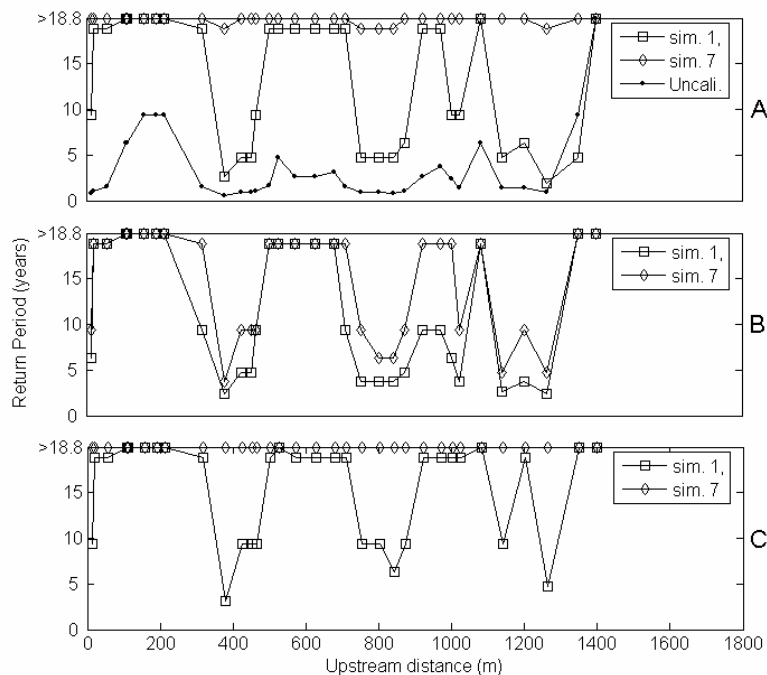


Figure 5 Surcharge frequencies in the Frejlev sewer system illustrated as a longitudinal profile of the main pipe. For sake of clarity only the results corresponding to simulation no. 1 and 7 are shown for each SRM. In addition the hydrologically uncalibrated SRM A is shown in the top plot.

## 5 DISCUSSION

In the present paper three different surface runoff models were compared. It was shown that simple hydrological SRM's (A and C) could be calibrated with regards to

zero-order errors, using two parameters: the hydrological reduction factor and initial loss. The more complex SRM B containing eighteen parameters could be hydrologically calibrated based on the calibration of SRM A and C. Contrary to SRM A and C, SRM B includes rainfall intensity dependency in the simulation of the runoff volume, but unfortunately no intensity dependency could be detected in the corresponding rain-runoff measurements, and therefore the advantages of SRM B could not be emphasized in the hydrological calibration. In addition to this it is shown that the hydrological calibration is crucial in order to get realistic and reliable overflow volumes. With regards to the hydrodynamic routing on the surface, it is shown that each of the three SRM's can be simplified containing only one parameter each. However, since no local runoff measurements have been conducted it is not possible to assess the hydrodynamic parameters based on measurements. Thus, a sensitivity analysis of the hydrodynamic parameters is conducted in order to investigate in what way occurrence of overflow, surcharge and flooding depend on the assessment of the hydrodynamic parameters. It is shown that the overflow volumes are practically independent on both choice of surface runoff model and parameter values. However the conclusion is opposite when surcharge and flooding are investigated. A remarkable change in surcharge frequencies with regards to choice of hydrodynamic parameters is shown, and the same is expected with regards to occurrences of flooding. Unfortunately no flooding occurs within the relatively short simulated period. As the SRM's are hydrodynamically uncalibrated it is not possible to determine if one model simulate the runoff hydrograph from the individual subcatchments more accurately, than the other. With regards to all three SRM's it is obvious that the shorter the transport time on the surface, the larger the peak flow in the drainage system and thus the smaller the return period of surcharge (-or flooding). With the aim of applying more accurate model simulations, the recommendation is to calibrate both runoff volumes as well as the temporal variations in the runoff flow. With regards to the latter, there is a need for further research in the runoff from local sub catchments and in the estimation of the local hydrodynamic parameters.

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## Paper IV

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### Probabilistic modelling of overflow, surcharge, and flooding in urban drainage using the First Order Reliability Method and parameterization of local rain series

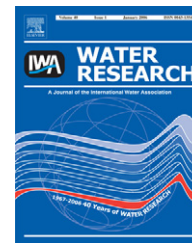
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# Probabilistic modelling of overflow, surcharge and flooding in urban drainage using the first-order reliability method and parameterization of local rain series

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## ABSTRACT

Failure of urban drainage systems may occur due to surcharge or flooding at specific manholes in the system, or due to overflows from combined sewer systems to receiving waters. To quantify the probability or return period of failure, standard approaches make use of the simulation of design storms or long historical rainfall series in a hydrodynamic model of the urban drainage system. In this paper, an alternative probabilistic method is investigated: the first-order reliability method (FORM). To apply this method, a long rainfall time series was divided in rainstorms (rain events), and each rainstorm conceptualized to a synthetic rainfall hyetograph by a Gaussian shape with the parameters rainstorm depth, duration and peak intensity. Probability distributions were calibrated for these three parameters and used on the basis of the failure probability estimation, together with a hydrodynamic simulation model to determine the failure conditions for each set of parameters. The method takes into account the uncertainties involved in the rainstorm parameterization. Comparison is made between the failure probability results of the FORM method, the standard method using long-term simulations and alternative methods based on random sampling (Monte Carlo direct sampling and importance sampling). It is concluded that without crucial influence on the modelling accuracy, the FORM is very applicable as an alternative to traditional long-term simulations of urban drainage systems.

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## 1. Introduction

An urban drainage model is an extensively used and powerful tool for the calculation of load capacity of urban drainage systems. In order to keep the system requirements, defined by respective authorities, the purpose of model simulations is mainly to determine the number of failures of a system in a given time period, where the failures can be defined as either overflows from combined sewer systems to receiving waters or the occurrence of surcharge or flooding.

In Denmark design of drainage systems is mostly based on simple deterministic calculation methods, e.g. the rational method, or the time–area method (Linde et al., 2002). In these methods statistical characteristics of several years of rainfall are used to determine the maximum capacity (i.e. full-running capacity), using simple hydraulic calculations for surface runoff and pipe flow, and given a specific return period of the rain. The pipe dimensions for the individual pipes are iterated manually until the full-running discharge corresponds to the calculated maximum discharge. For safety reasons dimensions are rounded to higher values. Using

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these methods, it is only possible to conclude that surcharge occurs with a larger return period than the return period of the employed rainfall. Flooding and overflow calculations are not included in both *design* methods.

Numerical hydrodynamic simulation tools (e.g. MOUSE, InfoWorks, SWMM, etc.) are often applied in *analysis* of drainage systems, either as brute force methods, in which long-term hindcast simulations of historical rain series are applied to determine return periods of surcharge, flooding and overflows, or in statistical methods, in which synthetic rain inputs, e.g. the Chicago Design Storm (CDS) (Kiefer and Chu, 1957), are used.

Both *design* and *analysis* methods are often impaired by errors and uncertainties, caused by uncertainties or errors in input data, parameters, etc. or by errors in the model methodology. Due to the uncertainty of the calculations or simulations, a certain safety is often implemented in order to prevent system failures due to the above-mentioned uncertainties. Uncertainties can in very simple cases be handled analytically, but if the context is more complex stochastic simulation techniques can be used, e.g. crude Monte Carlo simulation (direct sampling) or more sophisticated sampling techniques such as Latin hypercube sampling, importance sampling, stratified sampling or directional sampling. (Ditlevsen and Madsen, 1996; Madsen et al., 1986; Melchers, 1999; Tung and Yen, 2006; Tung et al., 2006)

This paper presents a new and alternative method for probabilistic analysis of drainage systems. The aim is to determine the system failure probabilities, considering surcharge, flooding and overflow as system failures. The method is based on hydrodynamical simulations with the commercial urban drainage model MOUSE, combined with a probabilistic method, namely the first-order reliability method (FORM) (Melchers, 1999). Applying statistical characteristics of several years of rainfall, it is possible to determine the system failures that are most likely to occur, i.e. the failures with the smallest return period. Moreover, an important advantage of this new proposed method is the possibility to include input and parameter uncertainties.

FORM has been extensively applied within the area of structural engineering and building technology (Melchers, 1999; Ditlevsen and Madsen, 1996; Madsen et al., 1986), and to some extent within the area of groundwater and river modelling as well as water quality modelling (Portielje et al., 2000; Schaarup-Jensen and Sørensen, 1996; Sørensen and Schaarup-Jensen, 1995, 1996), but as far as the authors know never in the context of urban drainage.

The rest of the paper is structured as follows: theoretical aspects of the methods used are presented in Section 2. In Section 3 the catchment used to exemplify the method is presented, and in Section 4 the variables that are applied are derived and parameters are estimated. The results are presented in Section 5, validated in Section 6 and discussed in Section 7. Concluding remarks are presented in Section 8.

## 2. Methodology

The principle of FORM is to find the probability of failure of a component in a given system. In this context failure is

defined as the occurrence of either overflow to receiving waters, or surcharge or flooding. In the predefined probability functions, FORM searches for the combinations of input values that are most likely to cause failure of the system. For doing so, FORM requires the failure space to be defined discretely (the combination of input values for which failure of the system occurs). The vector of the most likely values of input variables at the limit of the failure space is called the design point. As different parts of the system have different failure probabilities, separate analyses must be conducted for each investigated location of the system, and also separate analyses must be conducted depending on which of the three outputs (surcharge, flooding or overflow) is investigated. After the choice of outputs and definition of the failure space, the next step in a FORM analysis is to locate and choose the input variables for the analysis. Traditionally, urban drainage models contain numerous inputs and parameters, as several processes are modelled, e.g. hydrological surface processes, hydrodynamical surface runoff and pipe flow processes. Therefore, it is necessary carefully to choose the most important variables for the analysis, as it is impracticable to include all variables. The most important variables are often the global variables that are decisive for the whole system such as rainfall and surface variables, whereas local variables can be excluded initially in the analysis and set to fixed values.

When the input variables are chosen, these must be associated with probability density functions, and possible correlation between the variables must be derived (see Section 1).

### 2.1. The first-order reliability method

In this analysis, failure of an urban drainage system is defined whenever the water level in a given point exceeds a critical level within one rainfall event (or rainstorm). Statistical characteristics for one rainfall event are derived from a long rain time series. In a model set-up with  $i$  random variables, the limit of the failure space is also called the failure function (or limit state function) and is defined as an  $i$ -dimensional surface. In the FORM this multidimensional failure surface is approximated by a hyperplane in the standard normal space. The point on the hyperplane where the failure probability is the highest is labelled the design point. In Fig. 1 a theoretical example of a two-variable FORM analysis is shown, and as two variables are applied, the failure surface is a line.

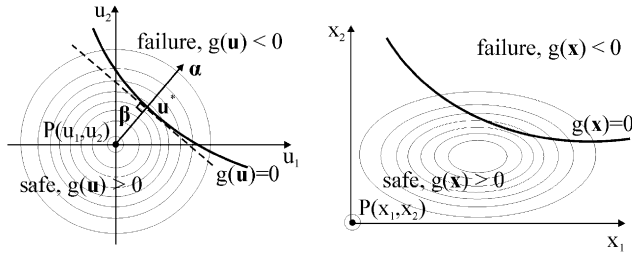
The failure surface (or limit state function) in this analysis is defined as

$$g(\mathbf{x}) = H_{\text{crit}}(\mathbf{x}) - H_{\text{max}}(\mathbf{x}) = 0, \quad (1)$$

where  $H_{\text{max}}(\mathbf{x})$  is the maximum water level in either an overflow structure or a manhole, and  $H_{\text{crit}}(\mathbf{x})$  is a critical water level, e.g. the crest level in an overflow structure or the pipe top level or the ground level in a manhole.  $\mathbf{x}$  is a vector of random variables. From this a value of  $g$  smaller than zero corresponds to failure.

The failure probability,  $P_f$ , within one rainfall event in the observation period  $P_t$  is defined as (Melchers, 1999)

$$P_{f,\text{FORM}} = P(g(\mathbf{x}) \leq 0) = \Phi(-\beta), \quad (2)$$



**Fig. 1 – Example of failure surface, design point and contours of the joint probability density function in the first-order reliability method with two variables. Left: failure surface and linear approximation in a standard normal space. Right: failure surface in the real space.**

where  $\Phi$  is the standard normal distribution function, and  $\beta$  is the Hasofer and Lind reliability index, which is the minimized distance perpendicular from the linearized failure surface (the point with the highest joint probability density) to the origin in a standard normal space (see Fig. 1, left).  $\beta$  Represents the point with the largest failure probability, given the probability distributions of  $\mathbf{x}$ , and is a measure of safety, e.g.  $\beta = 1$  corresponds to a failure probability of  $P_f = 15.8\%$ ,  $\beta = 2$  corresponds to  $P_f = 2.3\%$ ,  $\beta = 3$  corresponds to  $P_f = 0.1\%$ , etc.  $\beta$  is also called the *safety index*.

The FORM is based on standard normal independent variables, and all variables ( $\mathbf{x}$ ) have to be transformed into this standard normal space ( $\hat{\mathbf{u}}$ ). Initially, a transformation from dependent ( $\hat{\mathbf{u}}$ ) to independent ( $\mathbf{u}$ ) variables is implemented using Nataf transformation and Cholesky decomposition (Melchers, 1999):

$$\mathbf{u} = \hat{\mathbf{u}} \cdot \mathbf{T}^T, \quad (3)$$

where  $\mathbf{T}$  is the lower triangular matrix defined as  $\mathbf{T} \cdot \mathbf{T}^T = \boldsymbol{\rho}$ , and  $\boldsymbol{\rho}$  is the correlation matrix.

Secondly, transformation from the standard normal space ( $u$ -space) to the real space ( $x$ -space) is implemented using inverse transformation (Melchers, 1999):

$$\mathbf{x} = F_{\mathbf{x}}^{-1}(\Phi(\mathbf{u})), \quad (4)$$

where  $F_{\mathbf{x}}^{-1}$  is the inverse density function of  $\mathbf{x}$ .

From an initial guess of  $\mathbf{u}$ , a transformation to the  $\mathbf{x}$ -space is performed and the MOUSE model is evaluated with these values. FORM is based on an iteration procedure in which new values of  $\mathbf{u}$  are calculated until convergence of  $\beta$  and  $\mathbf{x}$  (or  $\mathbf{u}$ ) is obtained. In the following, the iteration number is labelled  $n$ , and the total number and iterations is labelled  $N$ . The total number of variables in  $\mathbf{u}$  are labelled  $I$  and the individual variables  $i$ .

Next the gradient vector of the limit state function is found, using a central finite difference approximation (Eq. (6)), with regard to every variable  $u_{i,n}$  where  $1 \leq i \leq I$  and  $1 \leq n \leq N$  (Melchers, 1999):

$$\nabla g(\mathbf{u}_n) = \frac{\partial g}{\partial \mathbf{u}_n}, \quad (5)$$

$$\nabla g(u_{i,n}) = \frac{\partial g}{\partial u_{i,n}} \cong \frac{\Delta g}{\Delta u_{i,n}} = \frac{g(u_{i,n} + du_i) - g(u_{i,n} - du_i)}{(u_{i,n} + du_i) - (u_{i,n} - du_i)}. \quad (6)$$

In order to find the gradient vector  $\nabla g$  the model must be executed twice for every variable.  $u_{i,n}$  is varied by addition and subtraction with  $du$ .

A unit normal vector to the failure surface is defined by (Melchers, 1999)

$$\alpha_n = -\frac{\nabla g(\mathbf{u}_n)}{|\nabla g(\mathbf{u}_n)|}, \quad (7)$$

where  $|\nabla g(\mathbf{u}_n)| = \left[ \sum_{i=1}^I (\nabla g(u_{i,n}))^2 \right]^{1/2}$  and  $I$  is the total number of variables.

Based on the unit normal vectors for all variables, it is possible to determine the reliability index (Melchers, 1999)

$$\beta_n = \sum_{i=1}^I -u_{i,n} \cdot \alpha_{i,n}, \quad (8)$$

from which it is possible to estimate an improved value of  $\mathbf{u}$  ( $\mathbf{u}_{n+1}$ ) by (Melchers, 1999)

$$\mathbf{u}_{n+1} = \alpha_n \cdot \left( \beta_n + \frac{g(\mathbf{x}_n)}{|\nabla g(\mathbf{u}_n)|} \right). \quad (9)$$

After  $N$  iterations (hopefully), convergence of  $\beta$  and  $\mathbf{u}$  (and  $\mathbf{x}$ ) is obtained. The convergence point for  $\mathbf{x}$  corresponds to the design point ( $x_1^*, x_2^*, \dots, x_I^*$ ), and the failure probability can be calculated using Eq. (2).

The return period of the event corresponding to the design point is easily calculated by

$$T = \left( P_f \cdot \frac{E}{P_t} \right)^{-1}, \quad (10)$$

where  $E$  is the number of events in a given period of time  $P_t$  and the number of failures per time period  $f_p$  (most often in years) is calculated by

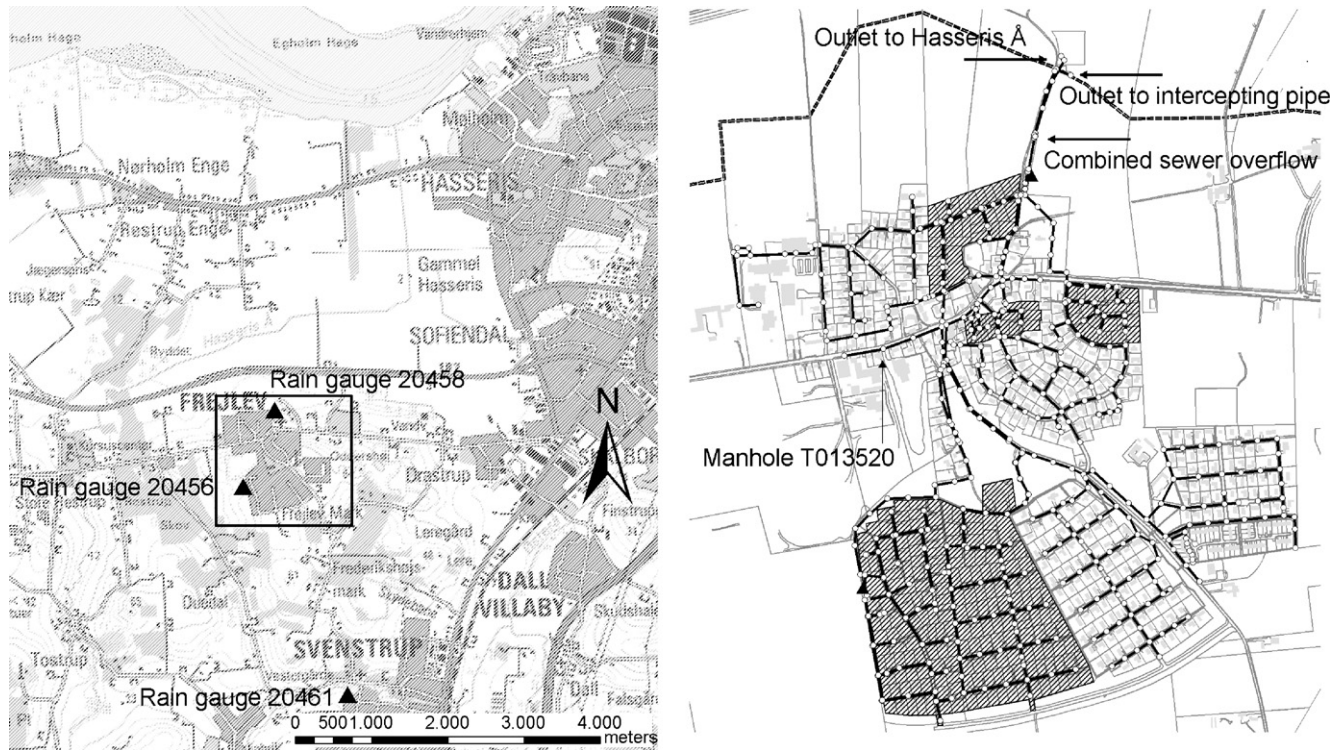
$$f_p = T^{-1}. \quad (11)$$

## 2.2. Random sampling methods

In order to validate the linear approximation of the FORM approach two random sampling methods are applied as well. In these, random values are sampled from the standard normal distribution and transformed to the real space as explained above. In the simplest approach, Monte Carlo direct sampling (DS) (also named crude Monte Carlo), random values are sampled from the whole standard normal distribution and the failure probability is calculated as (Melchers, 1999)

$$P_{f,DS} = \frac{1}{N} \sum_{n=1}^N I(g(\mathbf{x}) \geq 0), \quad (12)$$

where  $N$  is the total number of simulations and  $I$  is an indicator function ( $I = 1$  if failure and  $I = 0$  if no failure). Simulations are performed until convergence on  $P_f$ . This often requires a very large number of simulations. To decrease the number of simulations, and thus the simulation time, it is advantageous to limit the sample space to a subspace around the design point, which requires the design point to be assessed first, e.g. by FORM. This method is named Monte Carlo importance sampling (IS), and is useful in validating the approximation of the failure surface in FORM. The samples are drawn with a mean corresponding to the design point ( $\mathbf{u}^*$ )



**Fig. 2 – Left: Frejlev and surroundings. Right: the Frejlev drainage system. The hatching marks the area with separate sewer systems.**

and with a carefully chosen standard deviation ( $\sigma$ ). Thus, the failure probability, using IS, can be calculated as (Sørensen, 2004)

$$P_{f,IS} = \frac{1}{N} \sum_{n=1}^N I(g(\mathbf{x}) \geq 0) \cdot \frac{f_U(\sigma \cdot \mathbf{u}_n + \mathbf{u}^*)}{f_U(\mathbf{u}_n)} \sigma^n, \quad (13)$$

where  $f_U$  is the joint density function of the standard normal density functions.

### 2.3. MOUSE

The commercial urban drainage model, MOUSE 2005, is produced by the Danish company DHI Water & Environment and features advanced hydrological and hydraulic simulations of a complete urban catchment and drainage system. The model set-up applied in this paper is based on a well-calibrated set-up of the Frejlev catchment in the northern part of Denmark, as described in Schaarup-Jensen et al. (2005), Thorndahl et al. (2006) and Thorndahl and Schaarup-Jensen (2007).

As input and output files are in the ASCII format, it has been possible in this investigation to program a fully automated simulation process in application of FORM, DS and IS. All programming is performed in MATLAB.

### 3. Case: the Frejlev catchment

The case used in this paper is the Frejlev catchment. Frejlev is a small town with approx. 2000 inhabitants and a total catchment area of 87 ha. The drainage system is partly

separated and partly combined with a connected combined sewer overflow to the small stream, Hasseris Å. The overflow structure and attached in-line detention storage (pipe basin) were reconstructed in 1997 and are considered well functioning compared to the Danish standards. At a few locations in the catchment there are problems with flooding during high intensive rainfall (Schaarup-Jensen et al., 2005). The Frejlev catchment and drainage system are shown in Fig. 2.

### 4. Selection and parameter estimation of variables

The objective of this study is to acquire statistical characteristics of rainfall, which causes system failure (overflow, surcharge or flooding). Initially, three rainfall variables are investigated, namely the rainfall depth, the duration and the peak intensity (all per event). Through hindcast simulation with 18 years of rainfall input from the Svenstrup rain gauge, no. 20461 (DMI, 2006), the relationship between system failures and the three variables is investigated. In order to reduce the effect of the geographical variation of the rain, it would be preferable to apply one of the two rain gauges situated within the catchment (nos. 20456 and 20458), but as these rain gauges have been operated for 9 years only, it is chosen to only apply the Svenstrup rain gauge. In this analysis it is assumed that the rain is uniformly distributed over the catchment.

In Section 4.1 results of overflow simulations are presented and in Section 4.2 results of flooding and surcharge simulations are presented.



#### 4.1. Preliminary analysis of rainfall variables and overflow simulations

In Fig. 3 the relationship between the occurrence of overflow and the variables rain event depth ( $d$ ), duration ( $t_d$ ) and peak intensity ( $i_{p20}$ ) are presented. The latter is calculated as the maximum mean over 20 min, corresponding to the minimum system concentration time. Thus, fluctuations within 20 min will not affect the maximum water level in the overflow structure (combined sewer overflow).

The black line in Fig. 3, left, indicates the transition between events with no overflow and events with overflow. Related to FORM, this line corresponds to the failure surface, as it indicates the transition between the *safe* and the *failure* region in the real two-dimensional space with the variables depth and duration. This line can be interpreted as an *empirical failure surface*. The empirical failure surface is constructed such that the same number of events with overflow and events with no overflow occur above and under the line, respectively. This scatter indicates that the occurrence of overflow cannot be completely explained by the rainfall event depth and duration, which is clear when studying Fig. 3, right.

When analysing the drainage system, the strong linear correlation between the occurrence of overflows and the rainfall event depth and duration is obvious, as the large in-line detention storage is located just upstream of the overflow structure. This means this storage must be filled before overflow occurrence, hence a minor dependency on peak intensity contrary to the dependency on depth and duration.

The principle of using the rainfall event depth and duration for determination of system failures (overflow, surcharge and flooding) is presented in Vaes (1999) as the method of Kuipers. In the past, this method was used extensively in The Netherlands for design of drainage systems and combined sewer overflows.

Despite the dependence between the occurrence of overflow and the peak intensity, it is chosen to describe the rainfall characteristics only by the rainfall event depth and duration, as these variables obviously are the most important regarding the occurrence of overflow.

#### 4.2. Preliminary analysis of rainfall variables, flooding and surcharge simulations

In Fig. 4 the relationship between the occurrences of surcharge/flooding and the variables rainfall event depth ( $d$ ), duration ( $t_d$ ) and the peak intensity ( $i_{p10}$ ) are presented. As it is not possible to show results of all manholes in the sewer system only the most critical one was chosen, but other manholes follow the same pattern. Investigation of Fig. 4 shows that both the occurrence of surcharge and flooding is only dependent on the peak intensity.

Based on the above, it is chosen to simulate surcharge and flooding using only the peak intensity.

#### 4.3. Distributions of rainfall parameters

Willems (2000) investigated 27 years of Belgian rainfall, and discovered that rainfall intensities could be characterized by two-component exponential distributions at different aggregation levels. In this analysis the same approach is employed, not only with peak intensities but also with the variables depth and duration.

The cumulative distribution function for the two-component exponential distribution is correspondingly (Willems 2000)

$$F_2(x) = p \left[ 1 - \exp\left(-\frac{x}{\beta_1}\right) \right] + (1-p) \left[ 1 - \exp\left(-\frac{x}{\beta_2}\right) \right], \quad (14)$$

where  $p$  represents the percentile of the population of the first distribution.

Willems (2000) presents a method for calibrating theoretical distributions to empirical distributions, using adapted quantile-quantile plots (QQ-plots). In traditional QQ-plots, the inverse distribution functions of the theoretical and the empirical distribution are plotted on the abscissa and the ordinate, respectively. If the theoretical distribution fits the empirical distribution the points will approach the bisector. However, in the adapted QQ-plots, the exceedance probability is plotted on the abscissa and the inverse distribution

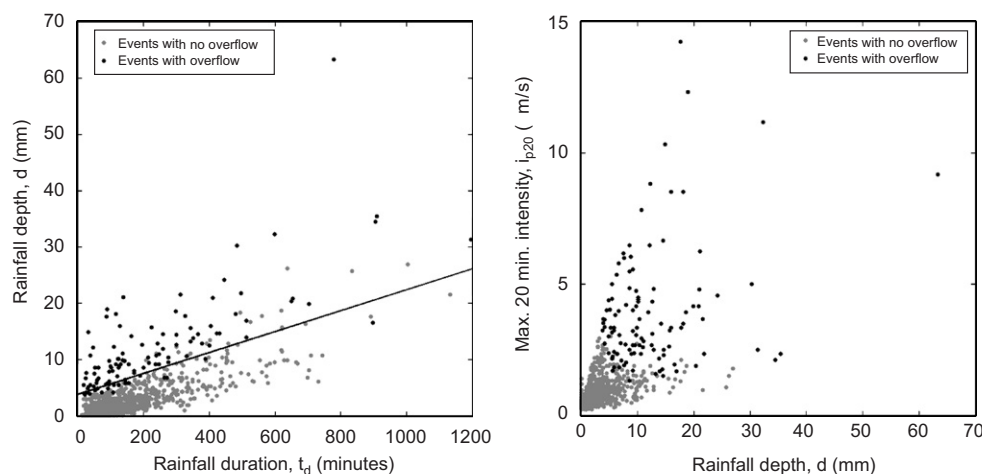
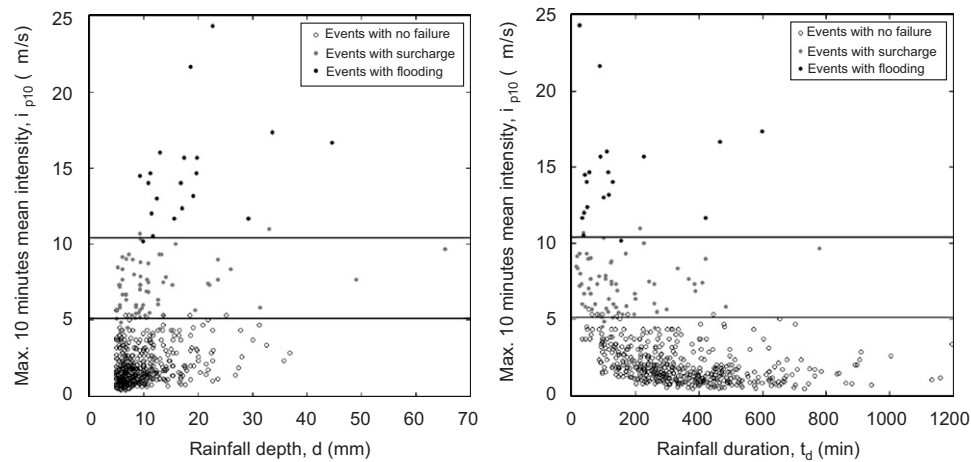
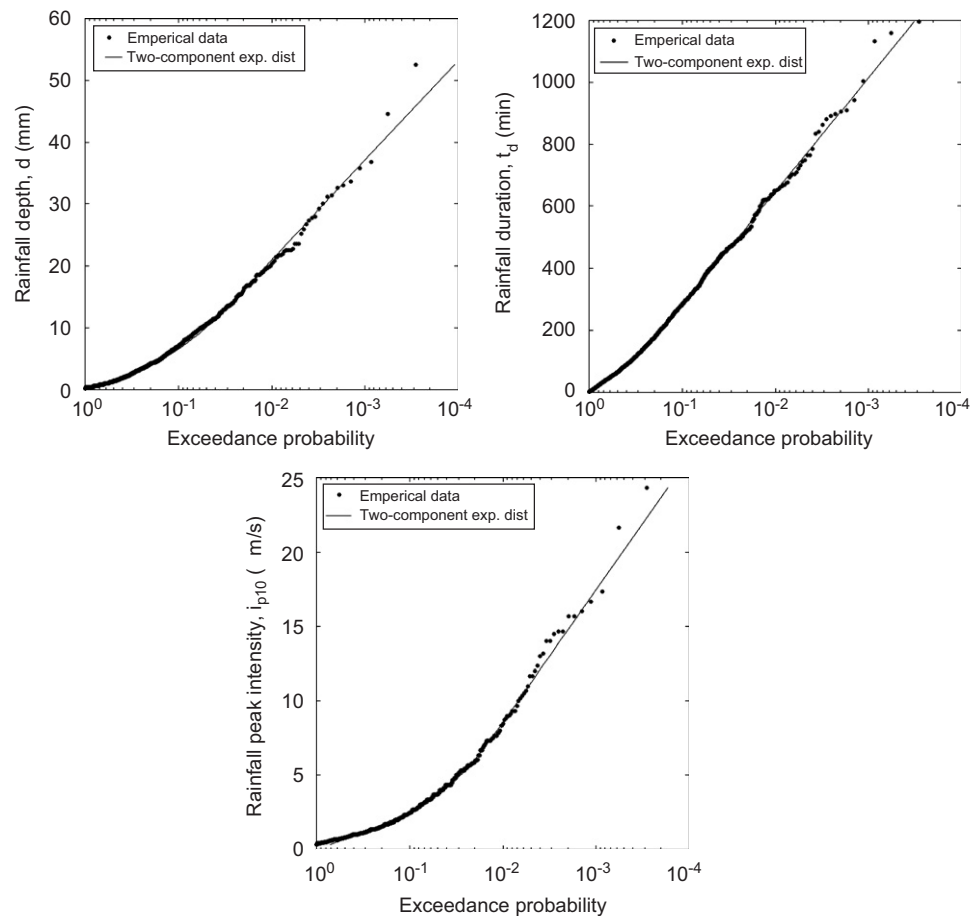


Fig. 3 – Occurrence of system failures (combined sewer overflows) as functions of the rainfall event depth and duration (left) and rainfall event depth and peak intensity (right).



**Fig. 4 – Occurrence of system failures (surcharge and flooding) in the most critical manhole (T013520) as functions of the rainfall event depth and peak intensity (left) and duration and peak intensity (right).**



**Fig. 5 – Calibrated distribution functions for the variables rainfall event depth, duration and peak intensity based on 18 years of measured precipitation with the Svenstrup rain gauge (no. 20461) (DMI, 2006). See Table 1 for parameter values.**

functions (both theoretical and empirical) on the ordinate. This methodology is very useful to study the tail (the extreme values) of the distributions, which is difficult with the traditional QQ-plots. The theoretical distributions are fitted by minimizing the mean square error. The results are presented in Fig. 5 (see Table 1).

As seen in Fig. 3 the variables depth and duration are dependent. The correlation coefficient between depth and duration is  $\rho_x = 0.78$ . When using the Nataf transformation (Section 2.1), the correlation coefficient in the standard space is required, and therefore the data are transformed to this space and the correlation coefficient yields  $\rho_u = 0.76$ .

#### 4.4. Generation of synthetic rainstorms

In order to employ the two selected variables for overflow simulations and the one variable for surcharge and flooding simulations in MOUSE, it is necessary to assume a general shape for the rainfall events. In the present investigation Gaussian-shaped rainfall is assumed, following the concept of Willems (2001) for stochastic modelling of rain cells. Later in the current section, the errors introduced by this assumption are considered.

The rainfall intensity  $i(t)$  in the Gaussian-shaped synthetic rainfall events is generated with the following formula, where the duration ( $t_d$ ) is calculated by  $t_d = c_1 \cdot \sigma$  and  $\sigma$  is the standard deviation in a Gaussian density function:

$$i(t) = \frac{c_1}{t_d \sqrt{2\pi}} \exp\left(-\frac{(t - (t_d/2))^2}{2(t_d/c_1)^2}\right) d \cdot c_2. \quad (15)$$

The two constants  $c_1$  and  $c_2$  are calibration parameters, see Section 4.5.

In the generation of synthetic rainfall events, two different methods have been explored corresponding to the two types of system failures (overflow and surcharge/flooding). In the first method, the Gaussian shape is calibrated in order to match the rain event duration  $t_d$  and rain event depth  $d$ . In the second method, the standard deviation is calibrated using the peak intensity  $i_{p10}$ .

**Table 1 – Calibrated parameters from the two-component exponential distributions**

	$d$ (mm)	$t_d$ (min)	$i_{p10}$ ( $\mu\text{m/s}$ )
$\beta_1$	7.0	160	3.88
$\beta_2$	1.8	50	0.90
$p$	0.20	0.57	0.09

In order to compare the synthetic rainfall events with real measured events two examples are exposed in Fig. 6.

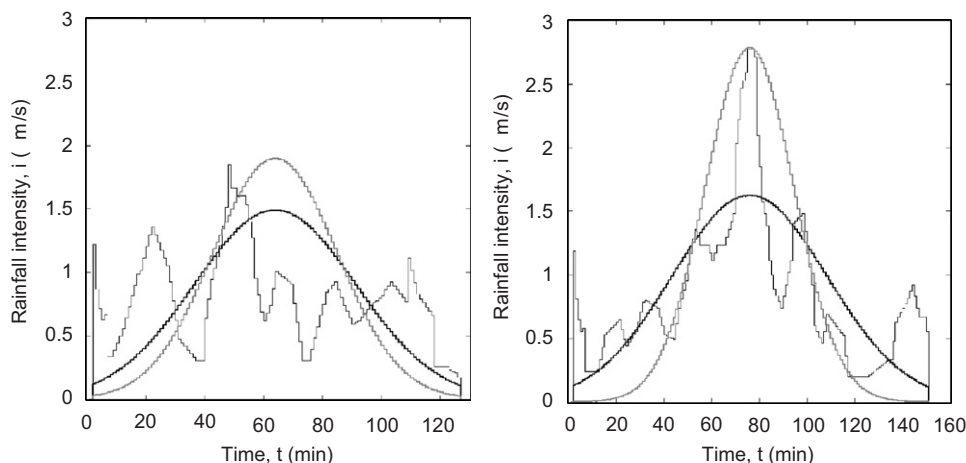
The preparation of the measured time series is based on the definitions of the Danish Committee for Waste Water (Spildevandskomiteen, 1999). The time series is based on data from tipping bucket rain gauges of the Rimco type, with a resolution of 0.2 mm. The intensities in the time series, with a temporal resolution of 1 min, are calculated by averaging over the time between two tips, and events are separated if the time between two tips is more than 1 h. In Fig. 6 a moving average over 10 min is applied, hence the match of the peak intensities.

Visually, the synthetic events and the measured events of Fig. 6 do not seem to fit very well, but in this context the fit is of minor relevance, provided that the residuals of critical water levels and overflow volumes between the real and the synthetic events are unbiased with small standard deviation. The errors introduced by the simplification of the event shapes are investigated in Section 4.5. In Denmark uniformly distributed rain (box-rain) is used in the dimensioning of pipes, detention basins, etc. (Spildevandskomiteen, 1999). This approach was attempted in the present paper, but the Gaussian-shaped rainfall events, based on Willems (2001), had smaller errors regarding estimation of water levels using synthetic rain events. Therefore the uniform-shaped events were rejected.

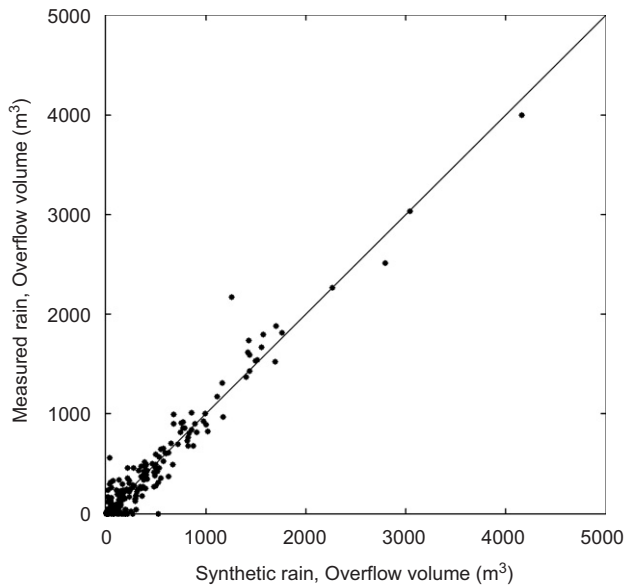
#### 4.5. Error estimation of overflow volumes and maximum water levels

With the purpose of investigating the error introduced by applying the synthetic rainfall events, simulations of all events in the Svenstrup time series are executed with the real measured rain and the synthetic, respectively, and the difference between the two are investigated regarding overflow volumes, cf. Fig. 7.

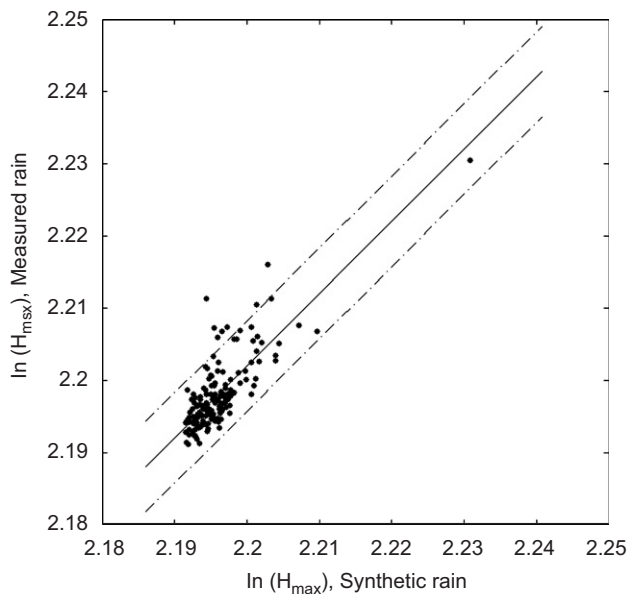
The scatter plot of Fig. 7 shows that there are some differences in the overflow volumes, due to the simplification



**Fig. 6 – Two examples of time series with measured (thin black), synthetic Gauss-shaped rainfall using variables event depth and duration (bold black), and synthetic Gauss-shaped rainfall using the event peak intensity (bold grey) and depth. The left and the right rainfall events have depths of 7.8 and 6.0 mm, respectively.**



**Fig. 7 – Simulations of overflow volumes with measured and synthetic rain events, respectively.**



**Fig. 8 – Simulations of maximum water levels with measured and synthetic rain events, respectively. The solid line indicates the mean value and the dotted lines indicate the 95% confidence intervals.**

of the rainfall, but by adjusting the calibration parameter  $c_1$  (cf. Eq. (15)), the bias is minimized, and hence the residuals are unbiased. The standard deviation is  $145 \text{ m}^3$ . The scatter indicates the same problem as presented in Section 4.1, that the two parameters, depth and duration, are not completely sufficient to describe the characteristics of the rainfall, but the error is not crucial. Therefore it is chosen to implement the error as a third variable in the simulation of overflows. This is practically implemented as an error term on the output, i.e. on the maximum water level. Plotting the maximum water levels in the overflow structure using real

and synthetic rain shows an increasing scatter for increasing  $H_{\max}$  (non-homoscedasticity), so in order to make the residuals normal distributed (constant scatter) different transformation methods are used, e.g. Box–Cox transformation (Box and Cox, 1964). The best transformation is obtained by an ln-transformation (corresponding to a Box–Cox transformation with parameter  $\lambda = 0$ ). The ln-transformation of the maximum water levels is shown in Fig. 8. Although the ln-transformed residuals are slightly skewed, a normal distribution is assumed to fit the data. The error term is implemented as a third variable using the following equation:

$$H_{\max} = \exp(\ln(H_{\max, \text{simu}}) - E_{H_{\max}, \ln}), \quad (16)$$

where  $H_{\max}$  is the corrected maximum water level,  $H_{\max, \text{simu}}$  is the simulated water level, using synthetic rain and  $E_{H_{\max}, \ln}$  is the error term, which is assumed to fit a normal distribution with mean 0.0020 and standard deviation 0.0031. Even though the residuals of the overflow volumes are unbiased there is a small bias on the estimation of the maximum water level.

Regarding surcharge and flooding simulations the error is also implemented as a variable. This error term is derived for the investigated manhole (T013520) and as the standard deviation is constant (independent on the water level), there has been no need of transformation of the data. Therefore the error term can be implemented as follows:

$$H_{\max} = H_{\max, \text{simu}} - E_{H_{\max}}, \quad (17)$$

where the error term follows a normal distribution with mean 0.007 and standard deviation 0.017 (Table 2).

## 5. Results

Regarding the overflow simulations, the FORM yields a design point corresponding to a rainfall event depth of 4.4 mm, a rainfall event duration of 58 min and an error term on the water level of  $-0.02 \text{ m}$ . This occurs with a failure probability of 5.8%, corresponding to 11.4 occurrences of overflow per year. The results are shown in Table 2 and illustrated in Fig. 9, with only the two variables depth and duration.

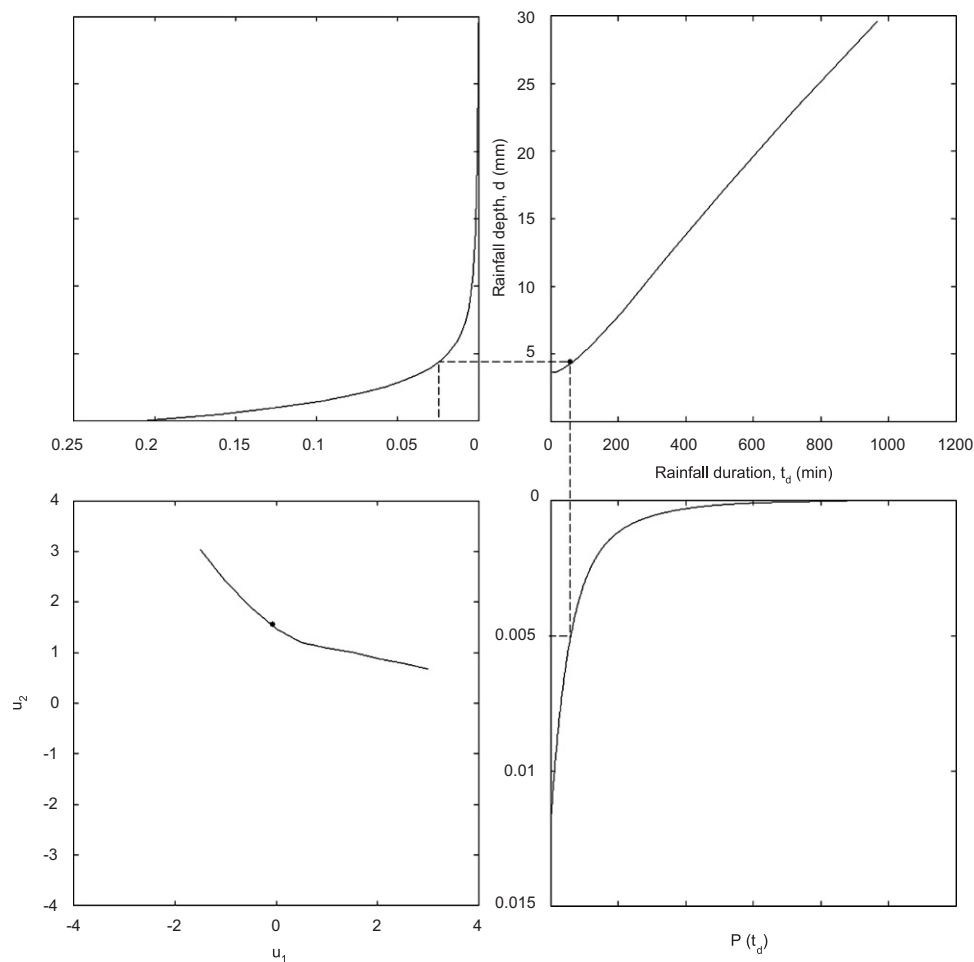
The results of the surcharge analysis with FORM are a design point with a rainfall event peak intensity of  $5.1 \mu\text{m/s}$  and no error on the maximum water level. The probability of failure is 2.8%, which corresponds to 5.4 occurrences of surcharge per year. The design point of the flooding simulations yields a peak intensity of  $9.7 \mu\text{m/s}$ , with no error on the maximum water. This corresponds to a failure probability of 0.7% and 1.4 occurrences of flooding per year. The results are shown in Table 2 and validated further in the next section.

## 6. Method validation

As the failure surface in the standard normal space is non-linear, and in order to validate the FORM approach in terms of the linear approximation of the failure surface, Monte Carlo IS around the design point is implemented. Additionally, a more traditional method of estimation the system failures, namely Monte Carlo DS is implemented in order to compare the number of simulations used in FORM, IS and DS. The results

**Table 2 – Results of the first-order reliability method**

Failure type	Combined sewer overflow	Surcharge (T013520)	Flooding (T013520)
Rain event depth $d$ (mm)	4.4	–	–
Rainfall event duration $t_d$ (min)	58	–	–
Rainfall event peak intensity $i_{p10}$ ( $\mu\text{m/s}$ )	–	5.011	9.73
Error term, water level $E_{H\max}$ (m)	–0.018	–0.0028	–0.0002
Iterations	168	30	40
Safety index $\beta$ (–)	1.572	1.915	2.44
Failure probability $P_f$ (–)	0.058	0.028	0.0074
Failure surface, $g(\mathbf{x})$	0.001	0.000	0.000
Failures per year FPP (years)	11.4	5.5	1.4
Return period $T$ (years <sup>–1</sup> )	0.088	0.183	0.691



**Fig. 9 – The failure surface with regard to the density functions for the rainfall events depth and duration. The black dot marks the design point ( $t_d = 58$  min,  $d = 4.4$  mm), i.e. the point where the failure probability ( $P_f = 0.058$ ) is the highest. The left plot at the bottom shows the non-linear failure surface in the standard normal space.**

of the three different methods, regarding overflow simulations, are presented in Table 3 along with results of the traditional brute force approach, MOUSE long-term simulation (LTS), where all events in a rain are simulated continuously. In Table 4 the corresponding comparison is made regarding the estimation of the surcharge and flooding probabilities.

Firstly, it is obvious, comparing MOUSE LTS, IS and DS, that the return periods are approximately the same, which emphasizes that the method of parameterizing the rain is valid. Secondly, Table 4 shows a somewhat larger return period of overflow with FORM, which must be associated with the linear approximation of the failure surface. Despite the overestimation of the return period, it must be concluded that

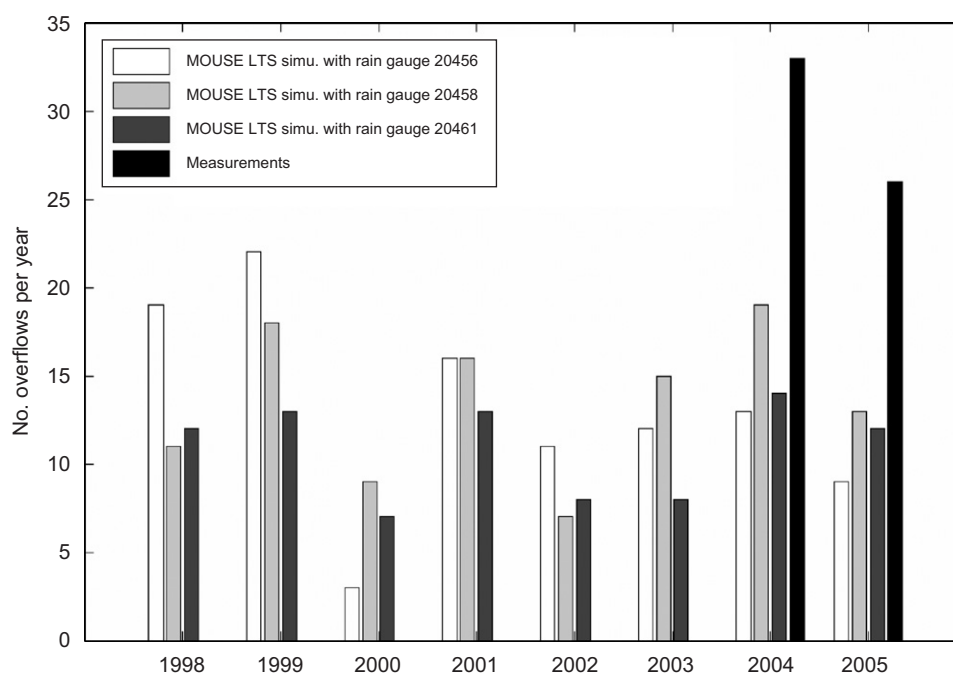


**Table 3 – Comparison of different methods, for estimation of overflow probabilities and return periods, at the combined sewer overflow**

	Failure probability, $P_f$	Mean no. of overflows per year, $f_p$	Return period, T (years <sup>-1</sup> )	No. of model runs
Traditional MOUSE LTS	–	12.3	0.081	–
FORM	0.058	11.4	0.088	168
IS	0.062	12.1	0.083	2000
DS	0.062	12.2	0.082	5000

**Table 4 – Comparison of different methods, for estimation of surcharge and flooding probabilities and return periods at manhole T013520**

	Failure probability, $P_f$	Mean no. of occurrences per year, $f_p$	Return period T (years <sup>-1</sup> )	No. of model runs
Traditional MOUSE LTS	–	1.1/4.8	0.90/0.21	–
FORM	0.007/0.028	1.4/5.5	0.69/0.18	40/12
IS	0.007/0.026	1.4/5.1	0.71/0.20	5000/1200
DS	0.009/0.026	1.7/5.1	0.60/0.20	10,000/2000

**Fig. 10 – Simulations of the number of combined sewer overflows per year using data from three different local rain gauges, and overflow measurements from Aalborg Municipality (2006).**

FORM results in quite a good approximation of the return period.

The flooding/surcharge shows, as it was the case in the overflow simulations, a good agreement between the traditional MOUSE LTS simulations and the sampling methods. In the surcharge simulations there is a tendency to underestimation of the return period using FORM, but the devia-

tions are not crucial. Comparing the number of simulations in the two sampling methods, it is obvious that the flooding simulations require more simulations, as the failure probability is much smaller.

In order to validate FORM, instead of using the sampling methods, another approach would be to approximate the failure surface by a multidimensional second-order polynomial,

cf. the second-order reliability method (SORM), but this method is not implemented in this research, as convergence of SORM empirically is difficult, due to the numerical assessment of the second-order derivatives.

## 7. Discussion

In order to validate the present approach in a greater context, a comparison of MOUSE LTS simulations applying local rain data from two other rain gauges in the period 1998–2005 are presented in Fig. 10. In addition to this, measurements of overflow occurrence in 2004 and 2005 from a measuring campaign conducted by Aalborg Municipality (2006) are presented as well. The measurements of overflow are not validated, and therefore the reliability of the measurements should be considered.

Comparing the overflow simulations based on the rainfall data used in the present analysis (the Svenstrup gauge, 20461) with the results based on the two other local rain gauges in Frejlev (20456 and 20458), there is a tendency to an underestimation of the yearly number of overflows, compared with the other two gauges, but also quite a large deviation between the two gauges, located only 1 km apart. The unvalidated measurements of overflow from Aalborg Municipality show almost twice the number of overflows compared with the simulated number of overflows. These deviations are not handled any further in the present paper, but it is concluded that, based on the above, there is a need for further investigation of uncertainties in the modelling approach. This can be done by implementing more variables in FORM, e.g. measuring uncertainty of the rain, uncertainties due to local geographical variation of rain, uncertainty on parameters as the Manning coefficient, the runoff coefficient, etc. This will be investigated in another paper.

No measurements of surcharge of flooding have yet been conducted. Therefore the only way to validate the FORM approach is to compare the results with the traditional MOUSE model.

An analysis as presented above is obviously based on the assumption that the rain measured in the past is representative in the future. This is, however, uncertain due to the imminent climate changes and the following potential and unpredictable changes in rainfall. A change in return periods of system failures is therefore possible, but this is not investigated in the present paper.

## 8. Conclusion

This paper has presented a new methodology for the parameterization of rainfall in analysis of failures in urban drainages systems. It is shown that occurrence of combined sewer overflows can be very well described by two rainfall event variables, depth and duration, whereas it is sufficient to describe occurrence of surcharge or flooding by one variable, the peak intensity per rainfall event. Using these variables it has been possible to generate synthetic rainfall events, applying a Gaussian shape for the rainfall event hyetograph. Comparing traditional MOUSE LTS simulations with Monte

Carlo direct sampling and importance sampling, based on the parameterization of the rain, the same results are obtained.

Furthermore, the first-order reliability method (FORM) has been applied, using parameterization of the rain. It is demonstrated that it is possible to implement the FORM on a study of overflow, surcharge and flooding of an urban drainage system, with an acceptable outcome.

Without crucial influence on the modelling accuracy, the FORM is very applicable as an alternative to traditional long-term simulations of drainage systems. It is advantageous as the simulation time can be reduced to approximately 1% of the simulation time of a traditional model. Furthermore, it is possible to implement uncertainties in FORM in order to assess the probability of failure of a drainage system even more accurately.

In the present study, results are demonstrated for one manhole regarding surcharge and flooding, but other manholes show the same tendencies. However, one should be aware that if more manholes were investigated, a separate model run would have to be executed for every manhole, contrary to traditional long-term models, where all points of the drainage system are investigated in one model run. Of course, in practical applications, one can limit this to carefully selected manholes.

The results of this study could easily be implemented on other urban catchments, although it should be taken into consideration that the method is only tested on a mainly gravitational urban catchment, and it is not clarified how the method would work on a catchment with many pumps.

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## Paper V

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### Probabilistic modelling of combined sewer overflow using the First Order Reliability Method

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## Probabilistic modelling of combined sewer overflow using the First Order Reliability Method

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### ABSTRACT

This paper presents a new and alternative method (in the context of urban drainage) for probabilistic hydrodynamical analysis of drainage systems in general and especially prediction of combined sewer overflow. Using a probabilistic shell it is possible to implement both input and parameter uncertainties on an application of the commercial urban drainage model MOUSE combined with the probabilistic First Order Reliability Method (FORM). Applying statistical characteristics on several years of rainfall, it is possible to derive a parameterization of the rainfall input and the failure probability and return period of combined sewer overflow to receiving waters can be found.

**Key words** | combined sewer overflow, First order Reliability Method (FORM), Monte Carlo sampling, MOUSE, uncertainties, urban drainage modelling

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### INTRODUCTION

Hydrodynamic urban drainage models for load prediction of drainage systems are frequently used by consulting engineers to determine if the system in question maintains the requirements defined by the authorities. The purpose of modelling is mainly to determine the number of failures in an urban drainage system during a given period of time, i.e. to attach return periods to different occurrences in the system, e.g. surcharge, flooding, or combined sewer overflow to receiving waters. However, inputs (boundary conditions), parameters, model structure, etc. are encumbered with uncertainties causing model outputs to be uncertain which affects the reliability of the return periods.

Defining an occurrence of a combined sewer overflow as a system failure, the aim of the paper is to determine the system failure probabilities and return periods. To quantify these, standard approaches make use of simulation of design storms or long historical rainfall series in a hydrodynamic model of the urban drainage system. In this paper, an alternative probabilistic method, the First Order Reliability Method (FORM), is investigated. To apply this method, a long rainfall time series is divided in

rain storms (rain events) and each rain storm is conceptualized to a synthetic rainfall hyetograph by a Gaussian shape with the parameters rain storm depth and duration (Willems 2001; Thorndahl & Willems 2007). Using a hydrodynamic simulation model, the failure conditions for each set of variables are predicted. The method takes into account the uncertainties involved in the rain storm parameterization and uncertainties related to the measurement of the rain as well as the geographical variation. In addition to these input uncertainties, a number of hydrological and hydrodynamical variables are selected and handled stochastically. In order to validate the FORM approach the analysis is also conducted using Monte Carlo Direct Sampling (MCDS) and Monte Carlo Importance Sampling (MCIS).

FORM has been extensively applied within the area of structural engineering and building technology (Madsen *et al.* 1986; Ditlevsen & Madsen 1996; Melchers 1999), and to some extent within the area of groundwater and river modelling as well as water quality modelling (Sørensen & Schaarup-Jensen 1995, 1996; Schaarup-Jensen & Sørensen

1996; Portielje *et al.* 2000), but as far as the authors know only in the context of urban drainage in Thorndahl & Willems (2007).

## METHODOLOGY

The concept of FORM is to find the probability of failure of a component in a given system. In the predefined probability distributions for each variable, the FORM algorithm searches for the combination of variable values which are most likely to cause failure of the system. This approach is unique compared to traditional long-term simulations of drainage systems as a parameterization of the rainfall input is conducted. Thus, it is possible to determine the frequency of combined sewer overflow (with uncertainty assessment) using much less computation time. Moreover, it is possible to add statistically based uncertainties to the rainfall input, which is traditionally difficult to apply to real measured rainfall input time series.

### The First Order Reliability Method

The present paper does not present the specific details of the FORM algorithm. For further details see Thorndahl & Willems (2008). In a model setup with  $i$  random variables the limit of the failure space is also called the failure function and is defined as an  $i$ -dimensional surface. In FORM this multidimensional failure surface is approximated by a hyperplane in a standard normal space. The point on the hyperplane in which the failure probability is the highest (corresponding to the vector of variable values which is most likely to occur) is labelled the design point ( $\mathbf{x}^*$ ). In Figure 1 a theoretical example of a two-variable

FORM analysis is shown. As two variables are applied, the failure surface is approximated by a line. Failure is defined whenever the maximum water level in the combined sewer overflow structure exceeds the overflow crest level:

$$g(\mathbf{x}) = H_{\text{crit}}(\mathbf{x}) - H_{\text{max}}(\mathbf{x}) = 0 \quad (1)$$

$H_{\text{max}}(\mathbf{x})$  is the maximum water level in the overflow structure, and  $H_{\text{crit}}(\mathbf{x})$  is the crest level.  $\mathbf{x}$  is a vector of random variables. From this, a value of the failure function  $g$  smaller than zero corresponds to failure (overflow). The failure probability,  $P_f$ , within one rainfall event in the observation period  $P_t$  is defined as (Melchers 1999):

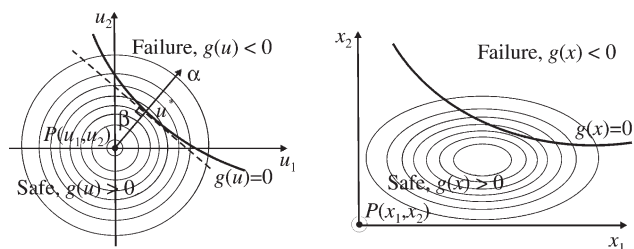
$$P_{f,\text{FORM}} = P(g(\mathbf{x}) \leq 0) = \Phi(-\beta) \quad (2)$$

$\Phi$  is the standard normal distribution function, and  $\beta$  is the Hasofer & Lind reliability index, which is the minimized distance perpendicular from the linearized failure surface (the point with the highest joint probability density) to the origin in a standard normal space (cf. Figure 1 left).  $\beta$  represents the point with the largest failure probability, given the probability distributions of  $\mathbf{x}$ . FORM is based on standard normal independent variables, and all variables in the standard normal space ( $\mathbf{u}$ ) are transformed into in the real space ( $\mathbf{x}$ ) using inverse transformation. From an initial guess of  $\mathbf{u}$ , a transformation to the  $\mathbf{x}$ -space is performed and the MOUSE model is evaluated with these values. FORM is based on an iteration procedure in which new values of  $\mathbf{u}$  are calculated until convergence of  $\beta$  and  $\mathbf{x}$  (or  $\mathbf{u}$ ) is obtained. The gradient vector of the failure surface is found using a central finite difference approximation for every variable. This means that the model must be executed twice for every variable. The return period of the event corresponding to the design point is calculated by:

$$T = (P_f \cdot E / P_t)^{-1} \quad (3)$$

$E$  is the number of rainfall events in a given period of time  $P_t$  and the number of failures per time period  $f_p$  (most often in years) is calculated by:

$$f_p = T^{-1} \quad (4)$$



**Figure 1** | Example of failure surface, design point and contours of the joint probability density function in FORM with two variables. Left: Failure surface and linear approximation in a standard normal space. Right: Failure surface in the real space.

A disadvantage of FORM is that it requires good initial guesses of variable values (especially if more than two

variables are implemented). The algorithm often finds a local minima on the failure surface instead of the global one.

Therefore, FORM is tested using a Monte Carlo direct sampling (MCDS) technique. Random values are sampled from the standard normal distribution and transformed to the real space as explained above. The failure probability is then calculated (Melchers 1999):

$$P_{f,MCDS} = \frac{1}{N} \sum_{n=1}^N I(g(\mathbf{x}) \geq 0) \quad (5)$$

$N$  is the total number of simulations, and  $I$  is an indicator function ( $I = 1$  if failure and  $I = 0$  if no failure). Simulations are performed until convergence on  $P_f$ . This approach can be used to validate the linear approximation of FORM, as the whole variable space is simulated. The MCDS approach samples the whole variable space, but in order to test the linear approximations in FORM it can be advantageous only to sample around the design point ( $\mathbf{u}^*$ ) with a specified standard deviation ( $\sigma$ ), using a Monte Carlo Importance Sampling (MCIS) technique (Sørensen 2004):

$$P_{f,MCIS} = \frac{1}{N} \sum_{n=1}^N I(g(\mathbf{x}) \geq 0) \frac{f_U(\sigma \cdot \mathbf{u}_n + \mathbf{u}^*)}{f_U(\mathbf{u}_n)} \sigma^n \quad (6)$$

$f_U$  is the joint density function of the standard normal density functions.

### Sensitivity measures

Using FORM, it is possible to define two different sensitivity measures to determine the relative sensitivity of every variable regarding the model output (Melchers 1999):

- The  $\alpha$ -vector is a unit normal vector to the failure surface at the design point, cf. Figure 1, left.  $\alpha_i^2$  is a measure of the percentage of the total uncertainty associated with the stochastic variable  $i$ . The sum of all  $\alpha_i^2$  equals 1. Total uncertainty refers to the total uncertainty implemented in this analysis. There might be other uncertainties which is not included.
- The omission sensitivity factor ( $\zeta_i$ ) determines the relative importance of the failure probability by assuming that the stochastic variable  $i$  is fixed, i.e. it is considered deterministic (Madsen 1988):

$$\zeta_i = \frac{1}{\sqrt{1 - \alpha_i^2}} \quad (7)$$

### Setup of the MOUSE model and randomization of variables

The commercial urban drainage model MOUSE 2005 (DHI 2005) features advanced hydrological and hydraulic simulations of a complete urban catchment and drainage system. The model setup applied in this paper is based on a well calibrated setup of the Frejlev catchment in the northern part of Denmark, as described in Schaarup-Jensen et al. (2005), Thorndahl et al. (2006), Thorndahl & Schaarup-Jensen (2007). The choice of variables in this paper is also based on these references. The model is divided in two sub models, the surface runoff model and the pipe flow model.

The hydrological part of the surface runoff sub model is governed by two parameters: (1) the *hydrological reduction factor* ( $\varphi$ ) determining the part of the impervious area contributing to the runoff and (2) the *initial loss* ( $i$ ) which is the hydrological loss due to wetting and filling of terrain depressions. These two parameters are considered global variables, i.e. the same value is implemented for every catchment. The *hydrological reduction factor* is also used to implement an error term on the rainfall input, see paragraph: *Conceptualization of rainfall input*. The flow routing on the surface can be modelled in different ways using the MOUSE model. In this paper the *Time Area model* is applied. This is based on a constant *concentration time* on the surface (DHI 2005). Values of this variable are sampled from a uniform distribution based on Thorndahl et al. (2008). All variables and distributions are presented in Table 1. The geometrics of the drainage system are based on technical maps from the Municipality of Aalborg. In the model setup these values are kept deterministic. Parameters related to the loss of energy are made stochastic, i.e. the friction loss in pipes (*the Manning number*) and the headloss in outlets from manholes. The pipes in the drainage system are of different materials with different roughness, e.g. plastic, smooth or normal concrete. The Manning number is considered a global variable, and therefore these are drawn fully correlated and normally



**Table 1** | Variables and chosen probability distributions

No.	Variable	Distribution	Parameters
1	Rainfall event duration, $t_d$ (min)	2-comp. exp.	$\beta_1 = 160, \beta_2 = 50, p = 0.57$
2	Rainfall event depth, $d$ (mm)	2-comp. exp.	$\beta_1 = 7.0, \beta_2 = 1.8, p = 0.20$
3	Error on rainfall event depth, $E_d$ (mm)	Normal	$\mu = 0, \sigma = 0.48$
4	Water level error, overflow structure, $E_{Hmax}$ (m)	Normal	$\mu = 0.002, \sigma = 0.003$
5	Hydrological reduction factor, $\varphi$ (–)	Normal	$\mu = 0.49, \sigma = 0.23$
6	Initial loss, $i$ (mm)	Uniform	$x_{min} = 0, x_{max} = 0.001$
7	Surface concentration time, $t_c$ (min)	Uniform	$x_{min} = 1, x_{max} = 10$
8	Manning number, $M$ ( $m^{1/3}/s$ )		
	Smooth concrete	Normal	$\mu = 85, \sigma = 5$
	Normal concrete	Normal	$\mu = 75, \sigma = 5$
	Rough concrete	Normal	$\mu = 68, \sigma = 5$
	Plastic	Normal	$\mu = 80, \sigma = 5$
9	Headloss factor, $K_m$ (–)		
	Round edged outlet	Uniform	$x_{min} = 0, x_{max} = 0.5$
	Sharp edged outlet	Uniform	$x_{min} = 0.25, x_{max} = 0.75$

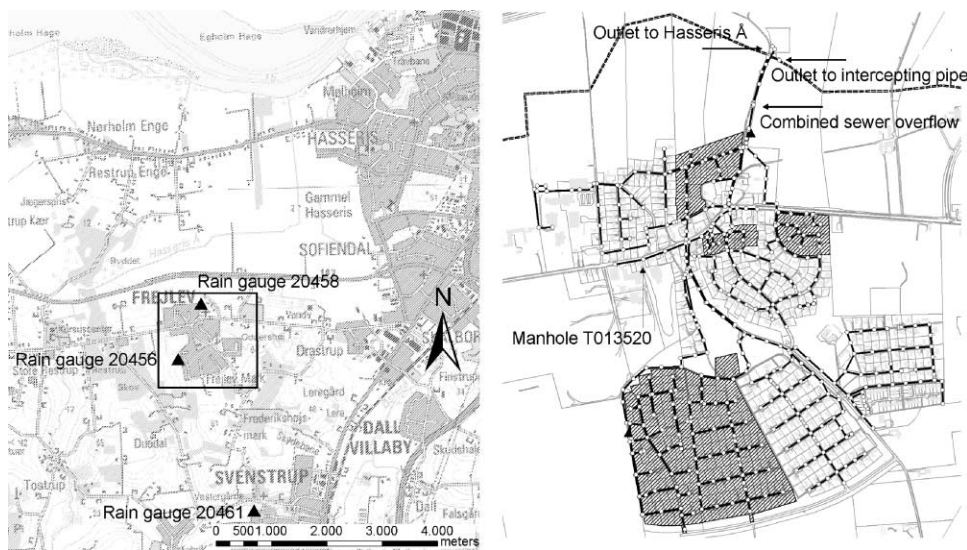
distributed. Values of the *headloss factor* are also drawn fully correlated depending on whether the outlet is round edged or sharp edged, but as no preferences are given to the distribution of the variable, a uniform distribution is applied.

### Conceptualization of rainfall input

In Thorndahl & Willems (2007) the rainfall event duration  $t_d$  and the rainfall event depth  $d$  are parameterized by two-component exponential distributions using 18 years of data from the Svenstrup rain gauge (no. 20461, Figure 2). It is shown that these two variables are the most important in modelling of combined sewer overflow. This is reasonable, at least in the Frejlev catchment, as a large inline retention basin is located just upstream from the overflow structure. This pipe basin fills up slowly and smoothes out the hydrographs, neglecting the peaks. Therefore it is primarily the runoff volume (the area under the hydrograph, given by the rainfall depth and duration) which induces the overflow. On the contrary Thorndahl & Willems (2008) shows that rain intensity peak values for different aggregation levels are decisive for modelling of surcharge and flooding in manholes.

By sampling correlated values from the exponential distributions it is possible to generate synthetic rain storm

events with a truncated Gaussian shape (Willems 2001). As this synthetic event is obviously a simplification of the real events, Thorndahl & Willems (2008) investigated the errors in the maximum water level prediction ( $E_{Hmax}$ ), introduced by this conceptualization. It was found that the errors could be parameterized by a normal distribution, in which the data was transformed with a Box-Cox transformation to account for heteroscedasticity (non-constant variance). The error introduced is of minor magnitude due to the overflow's primary dependence of the runoff volume and not the peaks. Thus, an event with more than one peak does not necessarily induce a larger error. One of the advantages of modelling with synthetic rainfall events is the possibility to implement uncertainties on the rainfall input. Two types of rainfall input uncertainty are considered in this paper. The first is the uncertainty introduced by not applying a geographical variability over the catchment. This uncertainty is implemented implicitly within the hydrological reduction factor (Figure 3), as the scatter around the regression line obviously is due to imperfectly uniform distributed rainfall events. The scatter is fitted to a normal distribution, cf. Table 1. The second type of rainfall input uncertainty is the uncertainty introduced when using a rain gauge which is not located within the catchment.



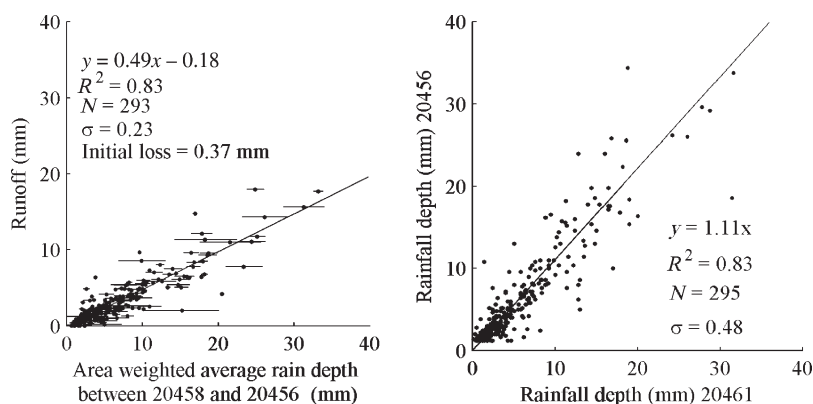
**Figure 2** | Left: The Frejlev catchment and surroundings. The black triangles are rain gauges. Right: close up of the Frejlev catchment. The hatching marks the areas with separate sewer system and the rest is a combined system.

The Svenstrup rain gauge (20461, Figure 2) is used for the parameterization of the rain as it is the longest of the local series. Using this gauge entails a small uncertainty due to its placement approximately 3.5 km from the centre of Frejlev. This uncertainty is investigated in Figure 3 (right), in which the rainfall depths from gauge 20461 are plotted against the depths from 20456, in a 9 year period. It is obvious that there is a small bias as well as some scatter. This error ( $E_d$ ) is implemented as an additional variable added to the synthetic rainfall depth  $d$ , as the scatter can be fit to a normal distribution. This variable clearly accounts

for some of the error in the geographical distribution of the rain fall input, thus this type of input uncertainty is treated as a lumped uncertainty.

## RESULTS

The first-order reliability method finds the design point ( $\mathbf{x}^*$ ), i.e. the set of variable values with the highest failure probability in terms of combined sewer overflow, corresponding to the values found in Table 2. It is seen that the rainfall event with the highest failure probability or smallest



**Figure 3** | Left: Calculation of the hydrological reduction factor and initial loss from an area weighted rain depth of two rain gauges. The runoff is calculated as the runoff volume per event divided by the impervious area. Horizontal lines indicate the individual values of the two gauges. Right: Event depth correlation between rain gauge 20456 (within the Frejlev catchment) and gauge 20461 (3.5 km from the centre of Frejlev).

**Table 2** | Results of the FORM analysis.  $x_i^*$  is the variable values in the design point and  $\alpha_i^2$  and  $\zeta_i$  are sensitivity measures (see the paragraph *Sensitivity measures*)

No.	Variable	$x_i^*$	$\alpha_i^2$	$\zeta_i$
1	Rainfall event duration, $t_d$ (min)	52.60	0.0186	1.0094
2	Rainfall event depth, $d$ (mm)	3.91	0.9163	3.4564
3	Error on rainfall event depth, $E_d$ (mm)	0.058	0.0095	1.0048
4	Water level error, overflow structure, $E_{Hmax}$ (m)	0.002	0.0001	1.0001
5	Hydrological reduction factor, $\varphi$ (–)	0.543	0.0553	1.0289
6	Initial loss, $i$ (mm)	0.000	0.0001	1.0001
7	Surface concentration time, $t_c$ (min)	5.49	0.0000	1.0000
8	Manning number (smooth concrete) $M$ ( $m^{1/3}/s$ )	85.1	0.0000	1.0000
9	Headloss factor (Round edged outlet) $K_m$ (–)	0.249	0.0000	1.0000

return period has a duration of 53 min. and a depth of 3.9 mm. The optimum of the hydrological reduction factor ( $\varphi = 0.54$ ) is somewhat larger than the mean value ( $\varphi = 0.49$ ). This is due to the large correlation with the rain depth. In order to maintain the same runoff volumes a small rain depth, which has the highest probability (cf. the exponential distribution), will cause a high value of the reduction factor. Examining the two sensitivity measures, the most important variable is by far the rainfall depth, which constitutes 92% of the total uncertainty. Subsequently, the rainfall duration and the hydrological reduction factor represent approx. 2% and 6% of the total uncertainty, respectively. The other variables are negligible in terms of combined sewer overflow. However, if this analysis was conducted on flooding in a specific manhole instead of overflow, the first and second order variables, concentration time, Manning number, and headloss is expected to be more important, as they are more decisive for the hydrograph peaks.

During the analysis it was observed that FORM requires a good choice of initial values in order to find the design point as the global minimum. Especially for the two variables concerning the rainfall input, as small changes in the values cause a great change in the probability due to the exponential distributions.

## DISCUSSION

Using FORM, a failure probability of 0.105 (corresponding to 20.5 failures per year) is predicted (Table 3). Validating

the method applying the MCIS simulations, a failure probability of 0.108 (corresponding to 21.1 failures per year) is found. This indicates that the fit of the hyperplane to the nine-dimensional failure surface is a valid method of finding the failure probability, despite the small deviation. The MCDS, which is considered the most reliable method of the failure predictions (as the whole variable space is sampled), deviates insignificantly from MCIS.

One might consider using the second order reliability method (SORM) instead, which is based on a multidimensional second order polynomial approximation of the failure surface, but as the errors introduced by linear approximations in FORM are small, this is not of interest. Furthermore, convergence of SORM is empirically even more difficult compared to FORM, due to the numerical assessment of the second order derivatives.

Since 2004 the municipality of Aalborg has registered the number of combined sewer overflows and their durations in Frejlev. 22, 17, and 25 overflows were registered in the years, 2004, 2005, and 2006, respectively

**Table 3** | Failure probabilities etc. with FORM, MCDS, and MCIS

	FORM	MCDS	MCIS
Failure probability, $P_f$	0.1045	0.1098	0.1075
Return Period, $T$	0.0487	0.0464	0.0473
Failures per year, $f_p$	20.5	21.5	21.1
No. of iterations	13*	–	
No. of model simulations	247	3000	500
Simulation time (hours)	2.1	25	4.2

\*The number of iterations is very dependent on the initial values of  $\mathbf{u}$ .  
The simulation time of a traditional long-term simulation is approximately 10 hours.

(overflow events with less than 1 hour in between are counted as one). This is in the same order of magnitude as predicted with the three methods and the measurements can therefore not be used to accentuate if one of the methods predicts the failure better than the other.

Despite the consistency between the predicted failures per year and the observed, some uncertainty is still associated with conceptualisation of the rainfall events, as the rainfall events are treated individually. In reality two small rainfall events within a short span of time might induce an overflow which is not considered in the present. However examining the rainfall time series this problem is rather insignificant as the system concentration time is in the same order of magnitude as the minimum time between events. Thus, the runoff is at a minimum when another rainfall events starts. The problem might be more significant for larger catchments with larger concentration times. In that case more events should be combined e.g. using a Poisson process (Willems 2001).

The choice of variables and their distributions are indeed empirical. This will affect the results of this analysis. However, some indication of a good and representative choice of variables and distributions is present, as the three techniques predict in the same order of magnitude as observed.

The return periods in this paper are only associated with the rainfall variables, i.e. all other variables are kept fixed in time. One might consider if a return period should be added to some other variables as well, e.g. the hydrological reduction factor, as this might also vary in time. This is, not investigated in the present paper.

Thorndahl & Willems (2008) showed that the method presented is very applicable in prediction of surcharge and flooding as well, but it is beyond the limits of this paper to describe this further. Nevertheless, this represents a potential alternative to simple design methods such as synthetic rain generation based on intensity–duration–frequency (IDF) curves or Chicago Design Storm (Kiefer & Chu 1957).

## CONCLUSION

It is concluded that the presented conceptualization of the rainfall input in an urban drainage model without crucial

affects on the modelling accuracy, can be used as an alternative to traditional long term predictions of combined sewer overflow. The First Order Reliability Method has been validated methodically using Monte Carlo Direct Sampling and Monte Carlo Importance Sampling, showing similar results. Thus, the simplifications in FORM are negligible in terms of predicting occurrences of combined sewer overflow. Moreover, it is observed that both FORM as well as the Monte Carlo sampling methods predict the number of overflows per year in the same order of magnitude as observed. Using FORM it is possible to reduce the simulation time to approximately 20% of the simulation time using traditional long-term simulations (Table 3).

The prediction of combined sewer overflow is shown to be very dependent on the rainfall input variables and to some extent on the hydrological surface variables, which are also the variables that contain the highest level of uncertainty. However, the variables that are governing the temporal flow variations in both surface runoff model and pipe flow model are shown to be negligible in prediction of overflow.

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## Paper VI

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### Event based uncertainty assessment in urban drainage modelling, applying the GLUE methodology

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# Event based uncertainty assessment in urban drainage modelling, applying the GLUE methodology

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## KEYWORDS

Urban drainage modelling;  
Generalized likelihood uncertainty estimation (GLUE);  
Uncertainty;  
Monte Carlo sampling;  
Calibration

**Summary** In the present paper an uncertainty analysis on an application of the commercial urban drainage model MOUSE is conducted. Applying the Generalized Likelihood Uncertainty Estimation (GLUE) methodology the model is conditioned on observation time series from two flow gauges as well as the occurrence of combined sewer overflow. The GLUE methodology is used to test different conceptual setups in order to determine if one model setup gives a better goodness of fit conditional on the observations than the other. Moreover, different methodological investigations of GLUE are conducted in order to test if the uncertainty analysis is unambiguous. It is shown that the GLUE methodology is very applicable in uncertainty analysis of this application of an urban drainage model, although it was shown to be quite difficult to get good fits of the whole time series.

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## Introduction

Reliable predictions of flooding, surcharge and combined sewer overflow (CSO) events from urban drainage systems using models are important in order to ensure that design criteria are kept. These design criteria, specified by local authorities, certify a safe urban infrastructure, little human inconvenience and minimal loading on receiving waters. Regardless of the good intentions in implementation of design criteria, the urban drainage models, and also simpler design methods, are, to a great extent uncertain, causing either exceedance of design criteria or unnecessary over-

dimensioning of drainage systems. Therefore, there is a need for more research in these uncertainties in order to make applications of urban drainage models more reliable.

Calibration of urban drainage models for non-research purposes are quite rare as observation data are hardly ever available and measurements are very expensive to conduct. Most consulting engineers use default model settings as the *best choice* of parameter values, causing the models to be potentially uncertain. Using a calibration of runoff volumes, Schaarup-Jensen et al. (2005) showed a remarkable difference between an uncalibrated (using default model values) and a calibrated urban drainage model, in predicted flooding frequencies as well as frequencies and volumes of combined sewer overflow (CSO) events to receiving waters.

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In the present paper a setup of the commercial urban drainage model MOUSE is conditioned on flow measurements and CSO occurrence data from a small urban catchment in Denmark. Applying the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992; Beven, 2001, 2006, 2008) a stochastic calibration and uncertainty analysis is performed. The calibration is based on six rainfall-runoff events from 2004, and the results are validated simulating three events from 2006. It will be investigated if the GLUE methodology can be used to estimate model parameters using a likelihood based on a measure of fitness. Furthermore, it will be investigated if the methodology can be used to study different types of uncertainties in the drainage model, e.g. uncertainties in inputs (boundary conditions), parameters, model structure, and conceptual uncertainties. Finally, the model sensitivity to model parameters will be investigated.

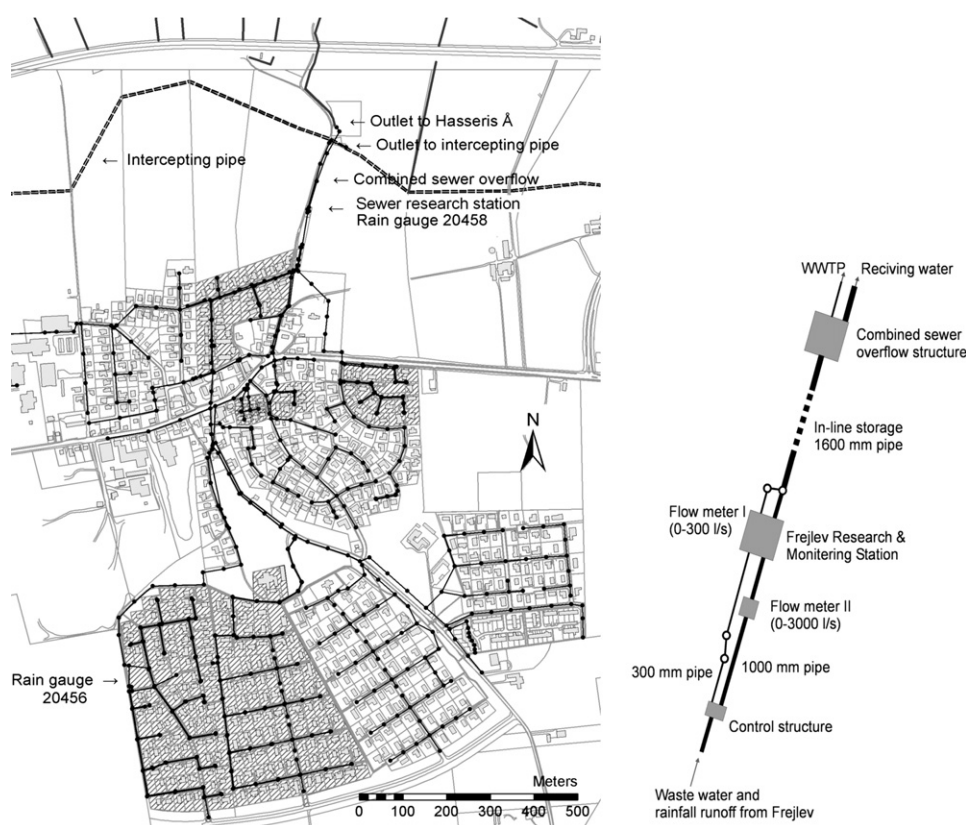
Several authors have investigated the area of uncertainties in urban drainage modelling, e.g. Thorndahl and Willems (2008), Thorndahl (2008) Korving and Clemens (2005), Grum and Aalderink (1999), Willems and Berlamont (1999), Lei (1996), but the GLUE methodology has, as far as the authors know, never been applied in hydrodynamic urban drainage modelling. The methodology has previously been used in integrated and urban water quality modelling (e.g. Lindblom et al., 2007; Freni et al., 2007; Mannina et al., 2006); in hydrological modelling of rivers and groundwaters (e.g. Freer et al., 1996; Beven and Freer, 2001a, Jensen, 2003; Jensen et al., 2004); and in hydraulic mod-

elling (e.g. Aronica et al., 1998; Hankin et al., 2001; Pappenberger et al., 2005; Pappenberger et al., 2006; Romanowicz et al., 1996; Romanowicz and Beven, 2003).

## The Frejlev catchment

Frejlev is a small town with approx. 2000 inhabitants and a total catchment area of 87 ha. The catchment is partly separated and partly combined with a connected combined sewer overflow to the small stream, Hasseris Å. The overflow structure (CSO) and attached in-line detention storage (pipe basin) were reconstructed in 1997 and are considered well functioning compared to Danish standards. The Frejlev catchment and drainage system are shown in Fig. 1.

The research and monitoring station in Frejlev (Scharrup-Jensen et al., 1998) is located upstream and close to the CSO structure where continuous high quality time series of both dry and wet weather flow are measured in order to gain general long term knowledge of the characteristics of both flow types. Upstream from the station, the sewer pipe system is divided into two: a 300 mm diameter "dry weather pipe" (observation point I) and a 1000 mm diameter "wet weather pipe" (observation point II). Within the station both pipes are equipped with high quality electromagnetic flow meters of the Parti-Mag type. According to the specifications of the manufacturer, both flow meters function with a maximum flow rate error of 1–1.5%. The flow gauge in observation point II is controlled by an internal



**Figure 1** Left: The Frejlev drainage system. The hatching marks the area with separate sewer systems. Right: overview of the monitoring station.

overflow structure (Fig. 1), and the gauge cannot detect flows smaller than  $0.05 \text{ m}^3/\text{s}$ .

Moreover, the flow gauges were calibrated and tested twice during the last eight years with equally low flow rate error. Despite the quite infrequent calibration, nothing indicates that the flow rate errors is larger than specified. The flow is measured every 20 s. Additionally, the Municipality of Aalborg has placed an on–off switch in the CSO-structure (observation point III). This switch logs binary data every 4 min indicating if there is overflow or not.

The flow measurements and overflow data are supplemented by two automatic rain gauge stations which are included in the Danish national rain gauge system managed by the Danish Waste Water Control Committee and operated by the Danish Meteorological Institute (2004). The rain gauge no. 20458 is placed next to the research station, 15 m above mean sea level. The second one (gauge no. 20456) is placed uphill, 55 m above sea level, in the south-western part of the town at a distance of approx. 1.2 km from gauge no. 20458 – cf. Fig. 1.

Measurements from this station have previously been used in various investigations e.g. volume calibration and flow measurements (Thorndahl et al., 2006; Schaarup-Jensen et al., 1998; Schaarup-Jensen et al., 2005), dry weather flow (Schaarup-Jensen and Rasmussen, 2004), conceptual model investigations (Thorndahl and Schaarup-Jensen, 2007), and uncertainty analysis using synthetic rain storm events (Thorndahl et al., 2008; Thorndahl and Willems, 2008).

## The generalized likelihood uncertainty estimation methodology

The generalized likelihood uncertainty estimation (GLUE) methodology makes use of a large number of Monte Carlo model simulations with random parameter sets chosen from prior probability density functions for each parameter. For each model simulation a likelihood measure is calculated in order to reflect the goodness of fit in comparison with some observation dataset. Simulations that are not considered to be acceptable are rejected as non-behavioural (given a likelihood of zero). From the remaining set of behavioural models, it is possible to derive posterior probability density functions for both parameters and predictions using the likelihood measure as a weighting factor. The intention is to allow for the demonstrated possibility that many different models and parameter sets might provide acceptable predictions when compared with the available observations: the equifinality thesis (Beven, 2006).

GLUE differs from traditional Bayesian approaches to uncertainty analysis, in that the likelihood measure need not be based on a formal error model (although formal error models can be used as special cases within the methodology where the assumptions can be justified, e.g. Romanowicz et al., 1996). The only requirements of a likelihood measure are that it should increase monotonically with increasing goodness of fit and should be zero for models not considered acceptable. In urban drainage modelling the concepts of GLUE are advantageous, as it is quite difficult to differentiate between different sources of errors, e.g. input errors, model structural errors, observation data errors, parameter

errors, etc. By treating the different sources of error implicitly using the GLUE likelihood weighting approach, it is possible to assess the potential of the sample of behavioural models to simulate the observations with a minimal need for additional assumptions.

There are various ways of defining the likelihood measure and different measures for different modelling purposes. In modelling discharge time series Freer et al. (1996) and Beven and Freer (2001b) have shown that Eq. (1) is suitable – especially in fitting the peaks, which are considered the most important derived output from the time series regarding surcharge and flooding. Moreover, it ensures low volume errors. These are especially important in prediction of combined sewer overflow events. The empirical likelihood (L) of the observations (O) conditional on the model (M) is calculated for each of the two flow observation points ( $j = \text{I}, \text{II}$ ):

$$L_j(\mathbf{O}_j | \mathbf{M}_j(\boldsymbol{\Theta}, \mathbf{I})) \propto \exp\left(\frac{-\sigma_{\mathbf{M}_j - \mathbf{O}_j}^2}{\sigma_{\mathbf{O}_j}^2}\right) \quad (1)$$

$\boldsymbol{\Theta}$  is a set of parameters,  $\mathbf{I}$  is the input,  $\sigma_{\mathbf{M}_j - \mathbf{O}_j}^2$  is the variance of the residuals between model and observations and  $\sigma_{\mathbf{O}_j}^2$  is variance of the observations.

Eq. (1) is shown to have advantages in combining more likelihood measures for different periods and for different types of observations, as it is the case in this paper. Moreover, the exponential of the variance ratio accentuates the peaks, and weights them higher compared to local minima, which is also preferable as it is the peaks that are important in calculations of the loads in the drainage system. The likelihood varies between 0 and 1 as a variance ratio of 0, corresponding to a perfect fit, equals a likelihood of 1. As for large errors, the ratio going for infinity will equal a likelihood of 0.

The likelihood of the binary overflow data ( $j = \text{III}$ ) can also be calculated using Eq. (1). However, time sliding errors have been observed (perhaps due to a poor quality clock in the overflow registrations). This means that flow gauge times are not synchronised with the overflow registration times. Thus, a different likelihood was defined using only the overflow duration (dur), avoiding the effects of the time sliding, thus the time error is only related to the temporal resolution of 4 min:

$$L_{\text{III}}(\mathbf{O}_{\text{III}} | \mathbf{M}_{\text{III}}(\boldsymbol{\Theta}, \mathbf{I})) \propto 1 - \frac{|\text{dur}_{\text{M}} - \text{dur}_{\text{O}}|}{\text{dur}_{\text{O}}} \quad (2)$$

Eq. (2) equals a likelihood of 1 when the duration of modelled and observed combined sewer overflow are equal.

A combined likelihood of all observation points is calculated by multiplying the individual likelihood measures. The likelihoods are weighted equally.

$$L(\mathbf{O} | \mathbf{M}(\boldsymbol{\Theta}, \mathbf{I})) \propto 1L_{\text{I}} \cdot 1L_{\text{II}} \cdot 1L_{\text{III}} \quad (3)$$

Different weights of the three likelihood measures are presented in Section ‘Discussion of acceptability criteria and weighting of likelihoods’.

The posterior distributions (the likelihood of the model conditional on the observations) are calculated by weighting the prior ( $L_0(\mathbf{M})$ ) by the likelihood of the observations conditional on the model.

$$L(\mathbf{M}(\boldsymbol{\Theta}, \mathbf{I}) | \mathbf{O}) = L_0(\mathbf{M}) \cdot L(\mathbf{O} | \mathbf{M}(\boldsymbol{\Theta}, \mathbf{I})) / C \quad (4)$$

C is a scaling constant such that the cumulative likelihood over all behavioural models is unity. In several of the cited papers concerning the GLUE concept, the partitioning between behavioural/non-behavioural simulations is implemented by applying a threshold to the likelihood measure. Here, the threshold for the acceptable simulations is chosen to be  $L_j > 0.3$ ;  $j = I, II, III$ , before the rescaling of (Eq. (4)). This is a purely empirical value and in Section 'Discussion of acceptability criteria and weighting of likelihoods' it is discussed how the value of the likelihood threshold of acceptability influences the selection of accepted simulations as well as the resulting posterior parameter distributions and prediction intervals.

The likelihoods are calculated for the whole time series but also separately for the different events within the time series in order to investigate if the posterior distributions vary from one event to another. However the selection of accepted simulations is carried out solely applying the whole time series. When examining the individual events the same number of selected events are used, but for the simulations with the highest individual likelihoods.

Originally GLUE was developed as an extension of the Generalised Sensitivity Analysis concept of Hornberger, Spear and Young (Hornberger and Spear, 1981) in which the idea of *behavioural/non-behavioural* simulations was introduced. In this method the model sensitivity to individual model parameters are found based on a number of Monte Carlo samples with random parameter values. Criteria for *behavioural/non-behavioural* simulations are defined in the same ways as in the GLUE approach. Plotting the cumulative distribution function (cdf) for the set of behavioural simulations and the set of non-behavioural simulations, respectively, it is possible, by comparing the deviation between the two, to determine if the model output in question is sensitive to changes in parameter values. If little difference between the two cdf's is found the parameter is considered insensitive with regards to the model output, and on the contrary if a strong difference is present the parameter is considered sensitive. Applying the nonparametric *Kolmogorov–Smirnov d-statistic* (maximum distance between the two cdf's), a measure of sensitivity is introduced, i.e.  $d = 1$  is the most sensitive and  $d = 0$  is non-sensitive (Hornberger and Spear, 1981; Beven, 2008).

This sensitivity analysis is used to determine the relative importance of each parameter in the model structure (see Section 'Sensitivity analysis').

## The MOUSE model of Frejlev

The 560 manholes, links, and attached subcatchments in the town of Frejlev are modelled using the commercial MOUSE 2005 model from DHI software. The model is divided in two sub models, the surface runoff model and the pipe flow model. The former is based on a detailed and locally distributed catchment description (Thorndahl et al., 2006) in which the area and imperviousness of every subcatchment is accurately surveyed. The hydrological part of the surface runoff model is governed by two parameters, the *hydrological reduction factor* ( $\varphi$ ) determining the part of the impervious area contributing to the runoff and the *initial loss* ( $i$ )

which is the hydrological loss due to wetting of filling of terrain depressions in the beginning of a rainfall event. These two parameters are considered global variables, i.e. the same value is implemented for every sub-catchment.

The flow routing on the surface can be modelled in different ways using the MOUSE model. In this paper, two different conceptual setups of the hydrodynamic surface runoff model, namely the *time area model* (A) and the *kinematic wave model* (B) are compared to test if this analysis can be used to determine which model is better in predicting the observed time series. The time area model is based on a constant *concentration time* on the surface (DHI Water & Environment, 2004). In the kinematic wave approach, the flow velocity on the surface is calculated depending on the water depth ( $y$ ) using the continuity equation and the Manning equation. To reduce the dimensionality of the parameterisation of the surface runoff calculations, Thorndahl and Schaarup-Jensen (2007) and Wangwongwiroj et al. (2004) have suggested a simplification of the Manning equation, as it is practically impossible to determine effective values for surface slope ( $S$ ), catchment area ( $F$ ), length ( $L$ ) or Manning number ( $M$ ) for a combination of runoff sources from roofs, roads, pavements, etc.:

$$Q = M \cdot \frac{F}{L} \cdot S^{\frac{1}{3}} \cdot y^{\frac{5}{3}} = C_b \cdot F \cdot y^{\frac{5}{3}} \quad (5)$$

Therefore, the flow ( $Q$ ) is calculated applying only a surface runoff parameter ( $C_b$ ), the subcatchment area ( $F$ ), and the water depth ( $y$ ). By doing so, the surface velocity varies from subcatchment to subcatchment in the *kinematic wave* approach, but is kept constant in the *time area model*. Both the hydrodynamic parameters in the *time area model* and the *kinematic wave model* are considered global variables; hence the same value is used on every subcatchment. Prior distributions for all the applied parameters are shown in Table 1.

The geometry of the drainage system is based on technical maps held by the Municipality of Aalborg. In the model setup these values are kept constant. Parameters related to the loss of energy are made stochastic: the friction loss in pipes (*the Manning number*) and the headloss in outlets from manholes. The pipes in the drainage system are of different materials with different roughness, e.g. plastic, smooth or normal concrete. The Manning roughness coefficient is considered a global variable for each pipe material, drawn from normal distributions. Global values of the *head-loss factor* are only dependent on whether the outlet is round edged or sharp edged. The pipe flow model is a fully dynamic flow model based on the Saint Venant equations.

The boundary conditions of the model setup consist of the *dry weather flow*, DWF (waste water flow), and the *rainfall input* time series. The dry weather flow is modelled using a fixed diurnal pattern, based on Schaarup-Jensen and Rasmussen (2004). The accumulated diurnal flow per person equivalent is then sampled uniformly.

All stochastic parameters are assumed to be constant over the drainage network in all simulations. This assumption is discussed further in the discussion section.

The *rainfall input* is modelled according to two different conceptual approaches. First, using only one rain gauge (no. 20456, cf. Fig. 1) uniformly distributed over the catchment and secondly, using an area weighted rainfall input from

**Table 1** Parameters and prior sampling distributions

Parameter	Prior distribution
Hydrological reduction factor, $\varphi$ (—)	$U(0.3, 0.9)$
Initial loss, $i$ (mm)	$U(0, 0.8)$
Surface concentration time, $t_c$ (min) <sup>a</sup>	$U(0, 20)$
Surface routing parameter, $C_b$ ( $m^{-2/3}/s$ ) <sup>b</sup>	$U(0, 32)$
<i>Manning number (<math>m^{1/3}/s</math>)</i>	
Smooth concrete <sup>c</sup>	$N(85, 5)$
Normal concrete	$N(75, 5)$
Rough concrete	$N(68, 5)$
Plastic	$N(80, 5)$
<i>Head loss, <math>K_m</math> (—)</i>	
Round edged outlet <sup>c</sup>	$U(0, 0.5)$
Sharp edged outlet	$U(0.25, 0.75)$
Dry weather flow, DWF ( $l/(PE \times day)$ )	$U(90, 150)$

$U(x1, x2)$  is a uniform distribution with minimum  $x1$  and maximum  $x2$ .  $N(\mu, \sigma)$  is a Gaussian distribution with mean  $\mu$  and standard deviation  $\sigma$ .

<sup>a</sup> Setup A1 and A2 only.

<sup>b</sup> Setup B2 only.

<sup>c</sup> In the rest of the paper, only the smooth concrete Manning number is presented as values are drawn fully correlated. This is also the case for the round edged headloss.

two rain gauges (nos. 20456 and 20458, cf. Fig. 1). In Denmark it is common practice to only use one rain gauge, and if possible one located within the catchment. It is then assumed that the rainfall time series is representative for the whole catchment. By applying a weighted average from two gauges it will be investigated if the model predictions can be improved by applying two rain gauges.

The following nomenclature is applied for the different conceptual models:

A1: Time–area surface runoff model with one rain gauge time series as model input.

A2: Time–area surface runoff model with area weighted rain gauge time series as model input.

B2: Kinematic wave surface runoff model with area weighted rain gauge time series as model input.

The observed rainfall-runoff events applied in the present analysis are presented in Table 2. The events are selected according to a threshold of the event rain depth of 5 mm and that the data was recorded in all of the observation points during the event.

The first six events are used in the model conditioning in this analysis, and most results are based on these. Event nos. 7–9 are used as a validation of the results from the first events and are only executed with the B2 model structure that gave the best results. In this case “best” is defined as the setup with the most behavioural number of simulations.

The simulations in this analysis are conducted using the computer cluster software CONDOR, in which 10 personal computers are connected. As the simulation time of one model run (6 events) is approx. 20 min it is possible to do 700–800 simulations per day using all 10 computers.

## Results

For each conceptual model setup 10000 model simulations are performed. In order to check if the results are robust with respect to the number of model realisations, 20000 model runs are performed with setup A2. The Kolmogorov–Smirnov  $d$  between overflow volume cdf's with 10,000 and 20,000 simulations respectively is 0.009. As the deviation is less than 1% it is concluded that 10000 model runs are sufficient.

Figs. 2 and 3 illustrate the likelihood of every single simulation (represented by one dot) as a function of the different parameter values. These plots are commonly known as dotted plots. Comparing the two plots (the conceptual setup A1 and B2 respectively; A2 shows similar results, and is therefore not shown) the most conspicuous is the narrow peak of hydrological reduction factor. As stated in Section ‘The MOUSE model of Frejlev’, this parameter represents the part of the area effective in contributing to the runoff, and is therefore crucial to the total runoff volume. The peak value of the reduction factor corresponds somewhat to the mean of the event specific reduction factors (Tables 2 and 3). Deviations are obviously due to the influence of other parameters as well as the rainfall uncertainty. As setup A1 is modelled with one single rain gauge as input and A2 and

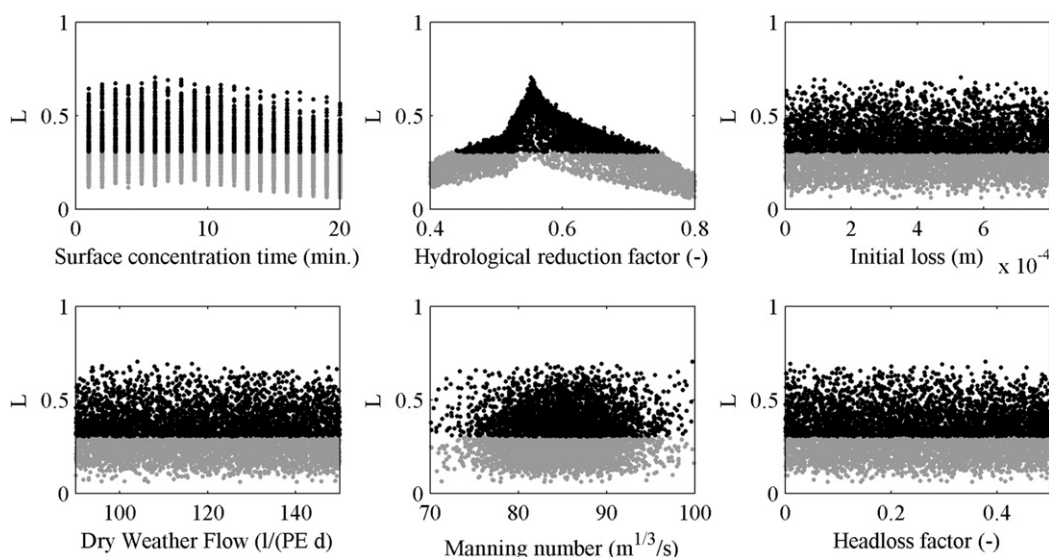
**Table 2** Rainfall-runoff events used for model conditioning

No.	Start time	End time	Rain depth, 20,456 (mm)	Rain depth 20,458 (mm)	Runoff depth <sup>a</sup> (mm)	Hydr. red. factor <sup>b</sup> (—)
1	21-June-2004 16:21	22-June-2004 21:26	24.0	26.2	11.7	0.47
2	23-June-2004 13:11	24-June-2004 06:42	12.8	11.8	8.0	0.65
3	15-October-2004 23:16	16-October-2004 16:23	7.2	7.4	3.9	0.53
4	22-October-2004 03:59	22-October-2004 19:36	6.4	9.8	3.3	0.41
5	22-October-2004 19:00	23-October-2004 07:44	16.4	18.8	12.1	0.69
6	29-October-2004 21:57	31-October-2004 09:29	26.0	23.6	17.6	0.71
7	22-May-2006 13:47	22-May-2006 19:20	5.2	10.6	2.6	0.33
8	26-September-2006 17:05	27-September-2006 01:00	10.2	10.2	5.0	0.49
9	13-November-2006 07:58	13-November-2006 14:50	5.8	7.0	3.0	0.47

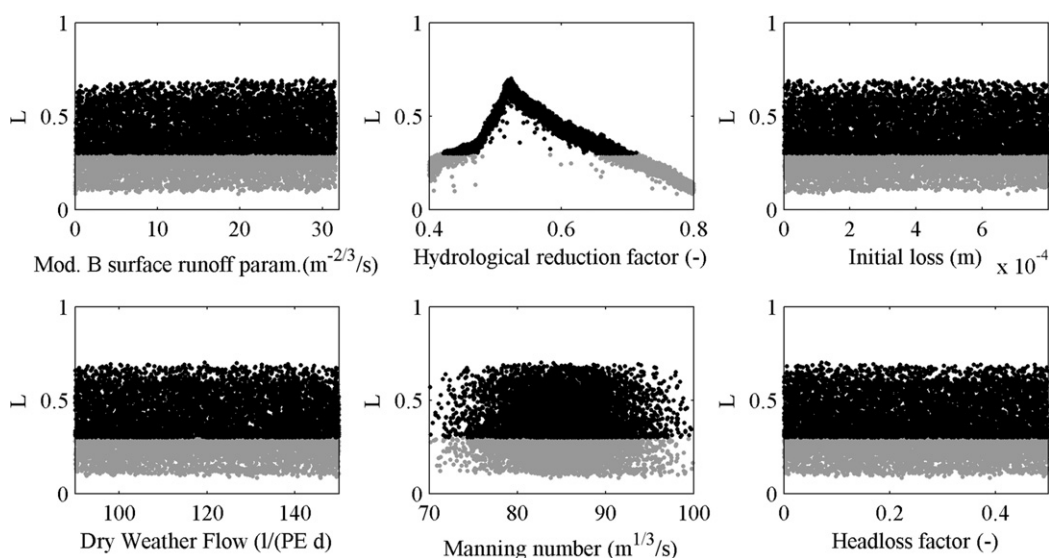
<sup>a</sup> The runoff depth is defined as the total storm runoff volume divided by the impervious area.

<sup>b</sup> The hydrological reduction factor is calculated as the runoff depth divided by the area weighted mean of the two rain gauges.





**Figure 2** Combined likelihoods over all calibration events as a function of parameter values, conceptual setup A1. Accepted simulations with  $L > 0.3$  are shown in black (3838/10,000),  $L_{\max}=0.704$ .



**Figure 3** Combined likelihoods over all calibration events as a function of parameter values, conceptual setup B2. Accepted simulations with  $L > 0.3$  are shown in black (6091/10,000),  $L_{\max}=0.700$ .

B2 are modelled with an area weighted rainfall input, the maximum likelihood of the reduction factor is slightly different comparing A1 with A2 and B2. This is an obvious result of the use of the reduction factor to compensate for uncertainties in the rainfall input. To investigate how the reduction factor varies from event to event, posterior values of this parameter are shown in Table 3 as the optimum value ( $\varphi_{\text{opt}}$ ), corresponding to the simulation with maximum likelihood per event per model setup. Also the behavioural minimum ( $\varphi_{\text{min}}$ ) and the maximum ( $\varphi_{\text{max}}$ ) of the hydrological reduction factor per event are shown. These bracket the values calculated from the observations for all the calibration events (Table 2).

The hydrological reduction factor is dominant in determining whether a model is behavioural or not in this applica-

tion. The other parameters initial loss, dry weather flow, pipe Manning number, and the headloss factor show a clear indication of equifinality, i.e. that it is possible to have the same maximum likelihood regardless of the parameter value (Figs. 2 and 3). This either indicates prediction insensitivity to parameters or that some parameters are interacting closely in producing behavioural models. For example, it could be possible that a low value of the Manning number was correlated to a high value of the headloss factor and vice versa to give equivalent likelihoods. However, plotting of the joint occurrences of two parameters shows no indication of strong interaction (not shown). See Section 'Sensitivity analysis' regarding the sensitivity of parameters.

In the conceptual setups A1 and A2 the surface concentration time represents the only parameter related to the

**Table 3** Posterior behavioural values of the hydrological reduction factor ( $\varphi$ ) based on the individual events as well as for the whole time series

Event	Setup A1					Setup A2					Setup B2				
	$\varphi_{opt}$	$\varphi_{min}$	$\varphi_{max}$	$L_{max}$	Figures	$\varphi_{opt}$	$\varphi_{min}$	$\varphi_{max}$	$L_{max}$	Figures	$\varphi_{opt}$	$\varphi_{min}$	$\varphi_{max}$	$L_{max}$	Figures
1	0.48	0.36	0.74	0.67		0.46	0.40	0.64	0.67		0.46	0.40	0.69	0.67	
2	0.55	0.45	0.74	0.79		0.56	0.52	0.75	0.80	15	0.58	0.47	0.74	0.80	
3	0.52	0.32	0.69	0.56		0.49	0.40	0.64	0.53		0.51	0.40	0.69	0.54	
4	0.49	0.32	0.83	0.80		0.44	0.40	0.64	0.80		0.40	0.40	0.74	0.77	4
5	0.55	0.53	0.83	0.76		0.52	0.50	0.64	0.79		0.52	0.49	0.75	0.80	
6	0.61	0.46	0.77	0.81		0.65	0.54	0.75	0.84		0.64	0.50	0.79	0.83	
1-6	0.55	0.44	0.75	0.70	2,10	0.52	0.48	0.64	0.72	3,11	0.52	0.42	0.71	0.70	3,9
7											0.41	0.32	0.70	0.67	
8											0.54	0.36	0.70	0.73	7
9											0.69	0.36	0.70	0.72	
7-9											0.51	0.38	0.61	0.68	6,10

temporal variation of the surface runoff. Examining Fig. 2 with the corresponding plot for setup A2 (not shown) there is a tendency for an optimum in the lower end of the parameter interval, i.e. better fits when the concentration time is approximately lower than 10 min. To some extent, this tendency is also present in setup B2 (Fig. 3), as larger values of the combined runoff parameter in surface runoff model B (Eq. (4)) corresponds to a faster runoff than if the value is low.

As stated earlier, one of the purposes of this paper is to determine if the different conceptual model setups can be distinguished in terms of model conditioning and if possible to determine if one model setup fits the observations better than the other. In setup A1, where data from a single rain gauge is applied as boundary condition 3838 simulations of the 10,000 (38%) is accepted, applying the likelihood threshold of 0.3. Correspondingly, 4390 of 10,000 (44%) are accepted in setup A2 with an area weighted mean of two local rain gauges. This difference indicates some improvement. With regards to setup B2, with area weighted rainfall input and the more complex surface runoff model, 6091 of 10,000 (61%) simulations are accepted, nearly twice the number of simulations compared to A1. The number of behavioural simulations is not necessarily a suitable measure of model goodness, as it depends very much on the choice of prior distribution ranges and threshold of acceptability. However, studying the time in which the observations are bracketed by the prediction intervals over all calibration events (not shown), a similar conclusion can be derived. In setup A1 the observations are bracketed 29% and 57% of the time in observation point I and II, respectively; in setup A2 the observations are bracketed 35% and 58% of the time in observation point I and II, respectively; and the corresponding values for setup B2 are 36% and 58%. It is worth noting that in GLUE the 90% prediction limits are not necessarily expected to bracket 90% of the observations in real applications, unless a explicit model of the residuals is added in defining the likelihood. Where they do not it is an indication that there are still improvements to be made, either to the model structure, or to the data that are used to drive and evaluate the model.

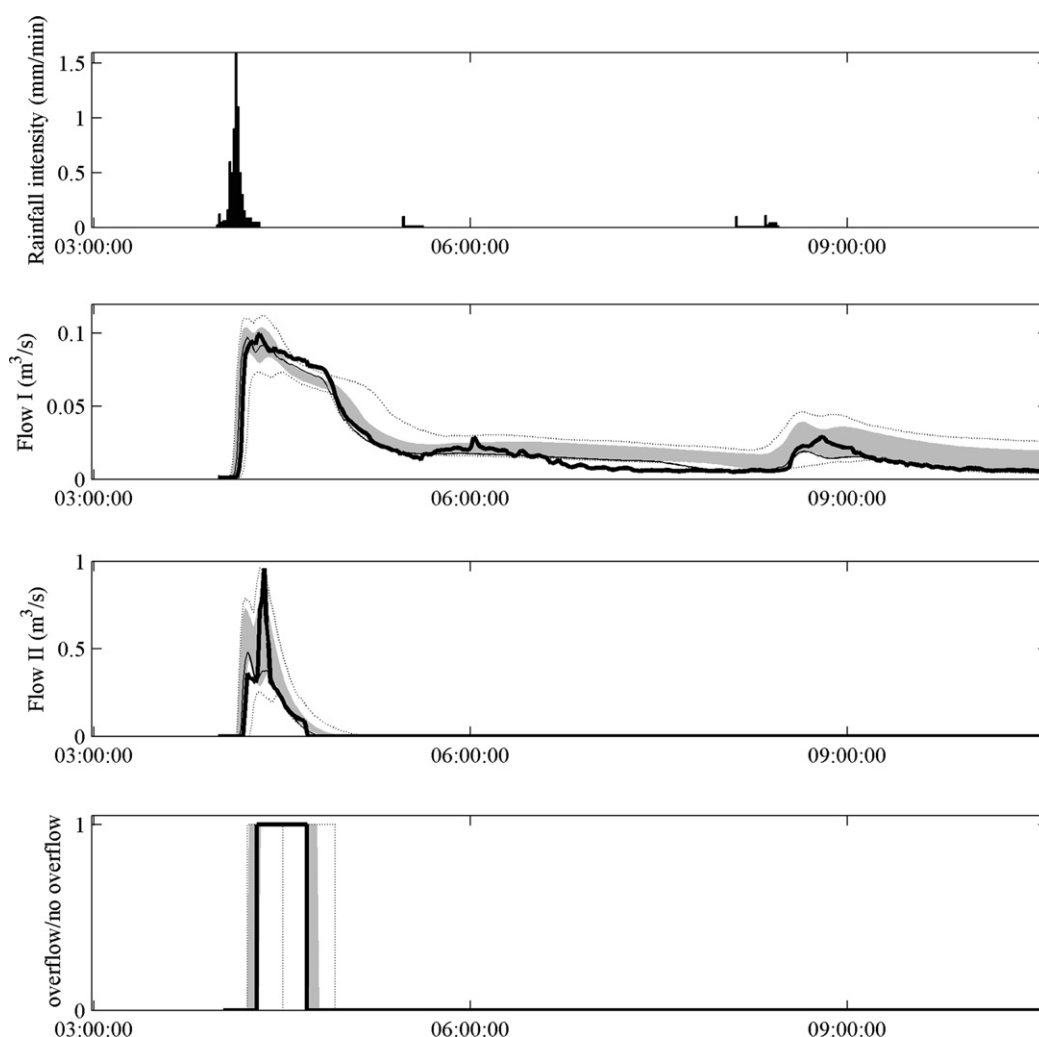
In Fig. 4, time series (event no. 4) of the observed and modelled flow in the two observation points, the observed and modelled overflow, and the rainfall input time series are shown for setup B2. Visually, it is difficult to distinguish between the time series plots of A1, A2 and B2, which is why the two former are not shown, however an indication of a poorer peak prediction, especially in observation point II, using setup A1 is present. Comparing the percentage of the time where the observations is bracketed by the prediction interval yields 60.1%, 65.1% and 65.7% in observation point I, setup A1, A2, and B2 respectively, and correspondingly 23.1%, 38.4%, and 53.9% in observation point II. In all of the setups the overflow duration is bracketed 100% of the time.

As stated in the introduction, the object of this paper is to assess uncertainties of combined sewer overflow volumes to receiving waters, as well as surcharge or flooding of the drainage system. In Fig. 5 the cumulative distribution function of overflow volumes in event nos. 1 and 4, modelled with the three conceptual setups, is plotted. The maximum water level in a critical manhole, which is often surcharged, is presented in Fig. 7 simulated with setup B2 (event no. 8).

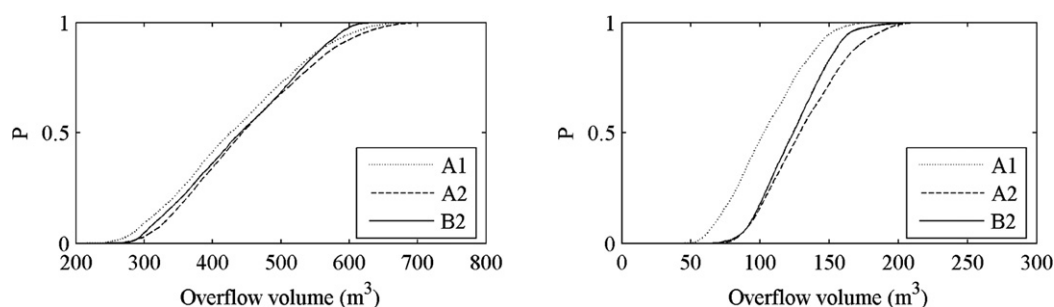
The difference in overflow volumes with regards to the model setups is rather insignificant. In event no. 1, the three setups fit almost perfectly, whereas in event no. 4, setup A1 differs a bit from the two others, but the variations are not significant. Therefore, it can be concluded that with regards to overflow volumes, the choice of conceptual model setup is not important. However, as setup B2 provides better predictions in bracketing the observations, this is selected as the "best" setup for use in validating the approach in the next section.

## Validation

By sampling from the posterior parameter distributions found in the previous section (event 1–6) a validation is conducted using three other events (7–9). As seen in the calibration the likelihoods depend very strongly on the value of the hydrological reduction factor. The posterior range (over all calibration events) of the hydrological reduction



**Figure 4** Event no. 4 simulated with setup B2. The bold black line is the observed time series, the thin black line is the simulation with the maximum likelihood, the grey area enclose the 5% and 95% prediction interval for the accepted simulations ( $L > 0.3$ ), and the dotted lines are the minimum and maximum of the prediction interval.



**Figure 5** Cumulated distribution functions of overflow volumes for accepted simulations ( $L > 0.3$ ) using the three conceptual model setups, respectively. Left: event no. 1, right: event no. 4.

factor for setup B2 is 0.42–0.71. Using the posterior distribution from the calibration as prior distribution in the validation causes the validation to fail, due to an optimum outside the posterior range of the hydrological reduction factor in event no. 7 (Table 3).

It is difficult to predict the value of the hydrological reduction factor antecedent to an event, as this param-

eter is used to compensate for a potential special distribution of the rain. Moreover, the hydrological reduction factor depends on the time between events, that is, on the water content in the soil on the semi- and pervious areas. By basing the validation priors on posteriors from only six events it is likely that other events will have optima outside the posterior ranges, so in order to find

useable posteriors, a larger number of events must be simulated.

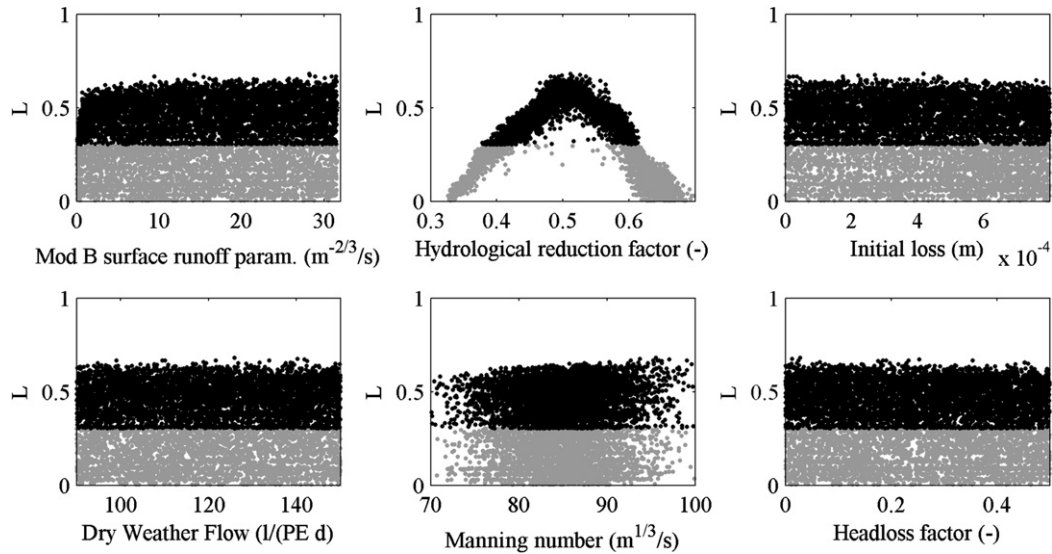
Owing to the validation failure, it was decided carry out the validation as a *second calibration*, in which the original priors is used (Table 1). In Fig. 6 the combined likelihoods are shown as functions of parameter values. The results are similar to the ones in the calibration; however the range of the hydrological reduction factor is wider, corresponding to the rain-runoff ratio of the specific events (see Tables 2 and 3).

In Fig. 12 the time series of event no. 2 are shown. In this case the model prediction is quite poor compared to event no. 4 (Fig. 4). The percentage of the time in which the observations are bracketed by the model prediction interval is for observation point I 11% and for observation point II 28%. This is concluded as a quite bad goodness of fit. Moreover the tail is strongly over predicted, which must be associated with either model structural errors or conceptual errors (see Section 'Discussion'). However, the two other events used for result validation display better tendencies.

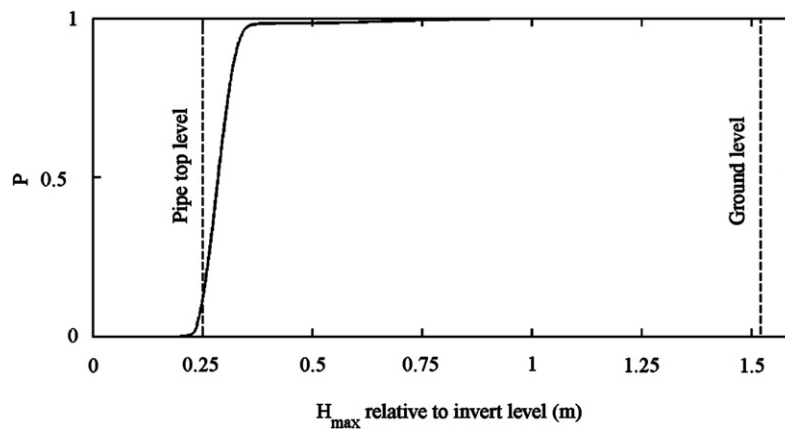
Fig. 7 presents a cdf-plot of the maximum water level in the previously mentioned critical manhole. Compared to the cdf-plots of overflow volume (Fig. 5) the prediction interval is quite narrow, varying approx. 10 cm (difference between 95% and 5% prediction interval). This indicates a rather small uncertainty on the maximum water level estimation; however, the prediction interval might be wider in other critical manholes.

## Discussion

Comparing the time series plots above, it is clear that even with the "best" conceptual setup, B2, the model is rather far from encapsulating the whole observed time series. However, the residuals are clearly not aleatory and there is a clear non-stationary bias. It would therefore be very difficult to provide a simple probabilistic error model for the residuals in a formal Bayesian approach to uncertainty estimation. The informal likelihood approach of GLUE is advantageous in this type of application in that it reveals such



**Figure 6** Combined likelihoods as a function of parameter values, conceptual setup B2 – validation events. Accepted simulations with  $L > 0.3$  are shown in black (5019/10,000),  $L_{\max}=0.682$ .



**Figure 7** Cumulated distribution function of water level in manhole no. T013520, event no. 8, conceptual setup B2.



model deficiencies. In particular, all the models tested perform somewhat poorly in predicting peaks and tails. The peaks are crucial in determining the maximum water levels in manholes (and are therefore important to be able to model correctly). In observation point II the peaks are under-predicted for almost every event. The tails are often over-predicted. Potential reasons for the model not being able to predict the observed time series perfectly, are presented in the following:

The flow gauge in observation point II is controlled by an internal overflow structure (Fig. 1), and the gauge cannot detect flows smaller than  $0.05 \text{ m}^3/\text{s}$ . This yields very steep rising limbs and tails, and as this is a clear observation error, the model cannot capture this phenomenon. This would be a good reason to discard time steps in which the flow is between  $0 \text{ m}^3/\text{s}$  and  $0.05 \text{ m}^3/\text{s}$  in observation point II. However, the error introduced by this measuring technique is of smaller magnitude related to flooding or combined sewer overflow, and therefore the time steps are not discarded.

Generally, the model seems to have a slower response than the observations, i.e. the model predictions are less dynamic compared with the observations. This may, at least in part, be the result of the rainfall input being uniformly distributed over the catchment. Uncertainties in the model input are probably the main reason why the predicted peaks at times are quite far from the observations. The fact that all parameters are treated as global variables might also cause a less dynamic response in the model predictions. The model would probably be more dynamic if some sort of spatial variation of these were introduced. One might imagine a more distributed model in which the catchment was divided into 5–10 smaller parts and parameters were drawn individually for each of these, perhaps with some correlation between the same parameters. This dramatically increases the dimensionality of the model calibration problem and the difficulty of identifying effective values of individual parameters. Fully distributed models are, in general, over-parameterised with respect to the information content of the observations available for calibration. If more independent information about effective parameter values can be made available, e.g. by water level observations in manholes around the catchment, a more distributed model might be implemented.

There is a possibility of some conceptual errors in the modelling of the internal overflow dividing the flow between observation point I and II (in control structure, Fig. 1). The overflow crest level is treated deterministically and the overflow time series are calculated by an empirical overflow formula. This crest level is very decisive for the volumes diverging to flow gauge I and II, respectively. A solution might be to implement the crest level as a stochastic parameter with some variance.

The overestimation of the tails must be related to some kind of model structural uncertainty, as the error is present when the rainfall has stopped. It was expected that this might be handled by implementing the more complex kinematic wave surface runoff model (B), compared with the simpler time area model, but this is clearly not the case.

More reasons for poor model performance might be associated with errors in the flow observations, but as stated in Section 'The Frejlev catchment' the manufacturer of the flow gauge promise a maximum error of 1–1.5% and the

gauges are tested and calibrated to this error level. The observation errors are therefore unlikely to be the reason for the poor model performance.

An important point to emphasize is that the uncertainty analysis conducted above is based solely on observations downstream in the drainage system. Therefore, it is only possible to condition the model on these points. If the model were to be made more reliable, some upstream observation points would be very beneficial. Moreover, the results would be more reliable if a larger number of events were simulated since the event specific uncertainties would be reduced, even though for parameters such as the hydrological reduction factor and initial loss an event to event variability should be accepted as presented above.

## Sensitivity analysis

In order to determine the importance of the chosen parameters, comparing the different conceptual setups and in the model in general, the model sensitivity to each parameter with regards to the number of accepted/non-accepted simulations are presented as described in Section 'The generalized likelihood uncertainty estimation methodology'. As stated, the nonparametric *Kolmogorov–Smirnov d-statistic* is applied as a measure of the sensitivity. Values of  $d$  close to 1 indicate a very high sensitivity, whereas a  $d$ -value close to 0 indicates low sensibility.

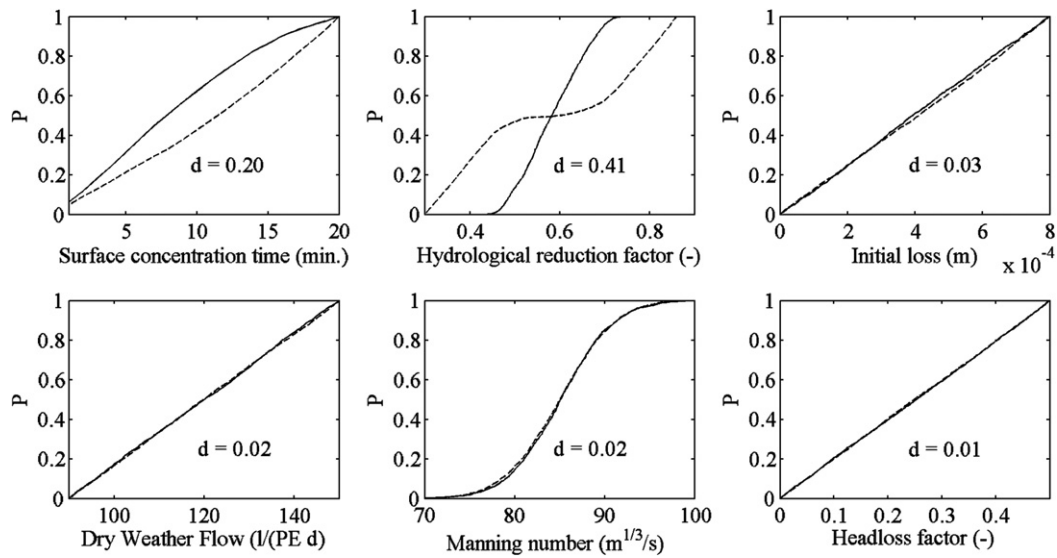
Examining results from setup A1 and B2 (Figs. 8–10; results from setup A2 is not shown) it is obvious that the most sensitive parameter is the hydrological reduction factor (with *Kolmogorov–Smirnov d*-values of 0.5 and higher). This is evident as the parameter value is fully correlated to the runoff volumes. In setup A1 and A2 the surface concentration time corresponds to a medium sensitive parameter with  $d$ -values of 0.2 and 0.3 respectively. However, the surface runoff parameter governing the temporal variation in the surface runoff in model B shows quite lower sensibility than the concentration time.

Besides the hydrological reduction factor, the other parameters affecting runoff volume, the initial loss, and the dry weather flow are very insensitive, corresponding to a low *Kolmogorov–Smirnov d*-value. The parameters affecting hydrograph shape, the pipe Manning number and the headloss factor are quite insensitive compared to the surface concentration time parameter.

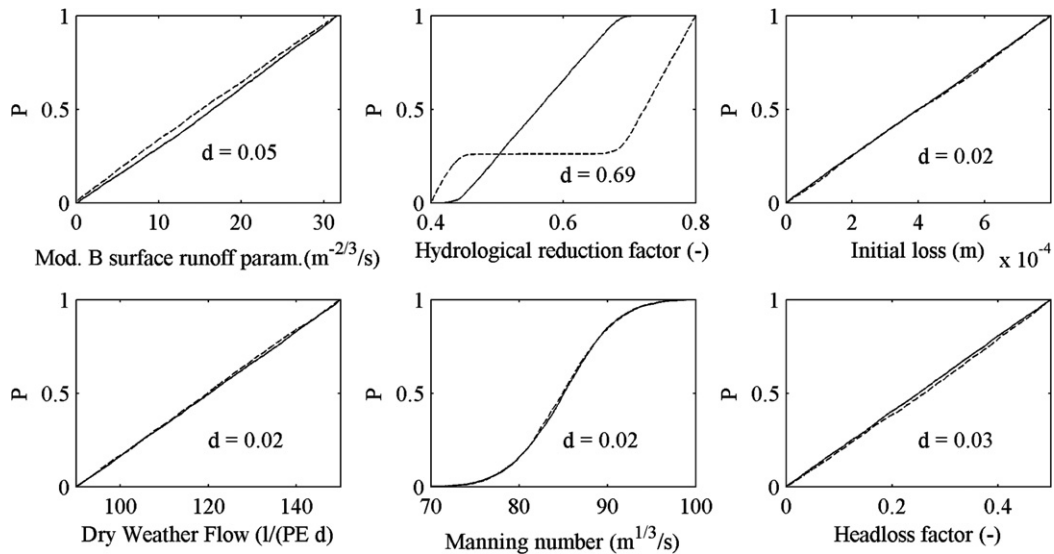
If the uncertainty analysis were to be conducted again the parameters initial loss, dry weather flow, Manning number and headloss, might be kept fixed, as their impact on model outputs appears to be minimal and, as noted earlier, there appears to be little interaction between these values in producing behavioural parameter sets.

## Discussion of acceptability criteria and weighting of likelihoods

The two main objectives in hydraulic urban drainage modelling are to simulate the maximum water levels in different manholes correctly in order to assess return periods for surcharge or flooding and to simulate the overflow volumes to receiving waters correctly. For the catchment of Frejlev Thorndahl and Willems (2008) showed that the hydrograph



**Figure 8** Sensitivity plots, Combined calibration event likelihood, setup A1. Solid distributions (posterior distributions) are the accepted simulations (3838/10,000) and dotted distributions are the non-accepted (6162/10,000).



**Figure 9** Sensitivity plots, Combined calibration event likelihood, setup B2. Solid distributions (posterior distributions) are the accepted simulations (6091/10,000) and dotted distributions are the non-accepted (3909/10,000).

peak values are the most important variables in determining the maximum water levels in manholes. However, the event duration and the total runoff volume are much more important variables regarding the overflow volumes.

To investigate how the model performs in terms of fitting the peaks and the runoff volumes, and how these are influenced by the choices of the likelihood threshold of acceptability as well as the weighting of the individual likelihoods from each of the three observation points, different approaches of acceptability are attempted in the following section. The main purpose of this uncertainty analysis is to test whether the models provide adequate predictions of the observations within the limits of uncertainty of both the data and the six parameters varied. If the observed flow time series are not bracketed by the

prediction intervals, this indicates other types of uncertainty, e.g. model input uncertainty or model structural uncertainty (or purely random uncertainty, though as noted earlier in this type of application the GLUE approach has an advantage of not compensating for obviously non-aleatory errors with a random error component). Consequently, it has been investigated how the weighting of likelihoods and thresholds of acceptability influence the prediction intervals in terms of bracketing the observations. The comparison between the different choices of acceptability is estimated using the key variables described below:

The *accumulated relative peak deviation* ( $E_{p,f,ob}$ ) between 5% and 95% model prediction fractiles of the peak ( $Q_{p,M,f,e,ob}$ ) and the observed peak ( $Q_{p,O,e,ob}$ ):

$$E_{p,f,ob} = \frac{\sum_e Q_{p,M,f,e,ob} - \sum_e Q_{p,O,e,ob}}{\sum_e Q_{p,O,e,ob}} \quad (6)$$

$Q_p$  is the discharge peak,  $f$  is the fractile (5% or 95%),  $e$  is the event,  $ob$  is the observation point (flow gauge I or II),  $M$  is the model,  $O$  is the observation.

The *accumulated relative runoff volume deviation* ( $E_{v,f,ob}$ ) between the prediction fractiles of the runoff volume ( $V_{M,f,e,ob}$ ) and the observed runoff volume ( $V_{O,e,ob}$ ):

$$E_{v,f,ob} = \frac{\sum_e V_{M,f,e,ob} - \sum_e V_{O,e,ob}}{\sum_e V_{O,e,ob}} \quad (7)$$

The *accumulated relative overflow duration deviation* ( $E_{dur,f}$ ) and the observed overflow duration:

$$E_{dur,f} = \frac{\sum_e dur_{M,f,e} - \sum_e dur_{O,e}}{\sum_e dur_{O,e}} \quad (8)$$

The percentage of time when the 5% and 95% model prediction fractiles bracket the observations ( $E_{t,ob}$ ).

In order for the model to be well-conditioned on the observations and to make sure that neither the peak, the volume nor the overflow duration are over predicted, the 5% prediction fractiles of the peak deviations, the volume deviations, and the duration deviations, should be negative. Thus the model prediction is less than the observation. Correspondingly, the 95% fractiles should be positive, representing that the model prediction is larger than the observation and under prediction is prevented. Obviously, the idea is to bracket observed peaks, volumes, and overflow durations with the smallest number of accepted simulations, resulting in the narrowest posterior parameter distribution. It might be argued that the relative deviations should be evaluated individually for every event and thus not accumulated, as there are obvious deviations within the individual events, however these results are not presented, except for one example in Fig. 11 (These are calculated using (6)–(8) for only one event, that is without summations.). In the following, different approaches of

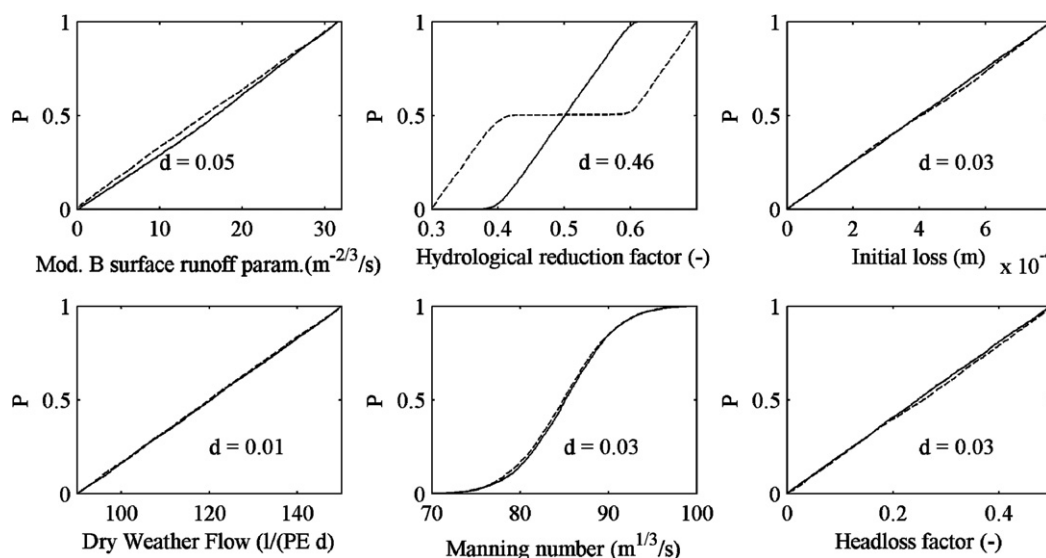
likelihood weighting and acceptability thresholds are presented based on the conceptual setup A2. Results are presented in Table 4.

### Equally weighted likelihoods

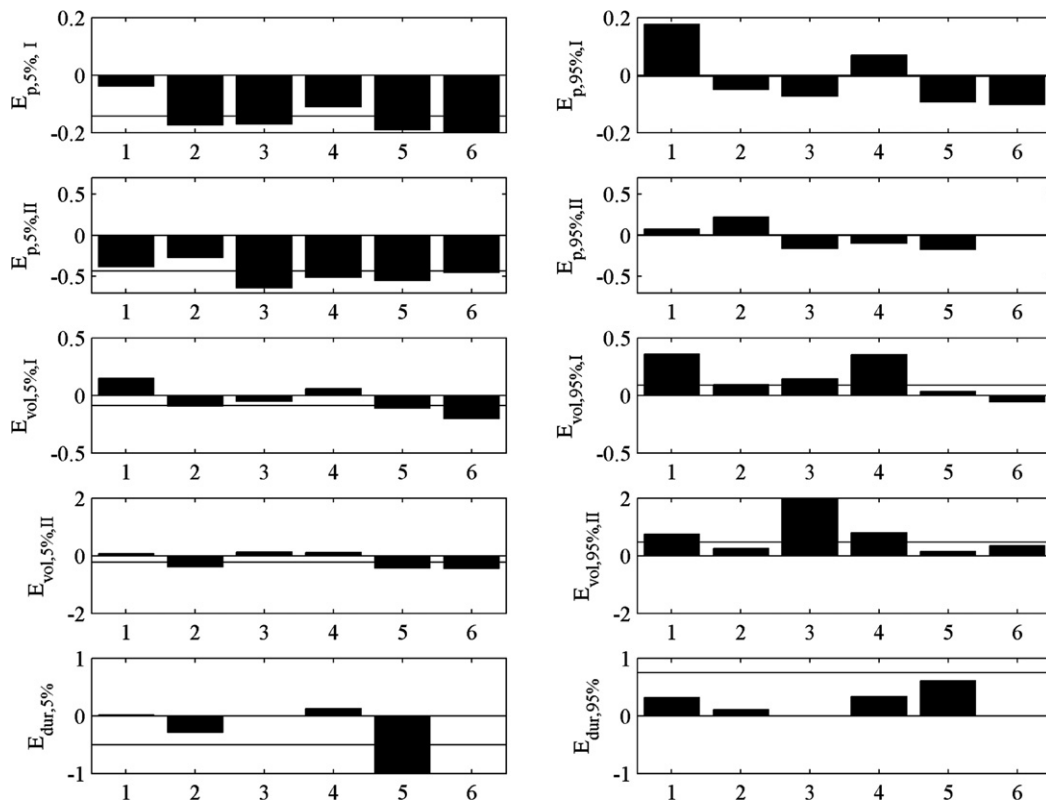
By weighting the three likelihood measures equally ( $L = 1 L_I \cdot 1 L_{II} \cdot 1 L_{III}$ ), no preference is given to either of the observation points. The following likelihood thresholds of acceptability are tested:  $L > 0.5$ , 0.4, 0.3, 0.2, and 0.1.

By comparing Table 4 no. 1–5, it is obvious that accepting simulations with a combined likelihood larger than 0.3 (accepting 8780 of 20,000 simulations) will bracket both peaks, volumes and overflow durations within the 5% and 95% prediction intervals. Despite the fit on the chosen key variables, only 35% of the observation data is within the prediction limits for the whole time series in observation point I and correspondingly 58% in observation point II. In Fig. 12 an example of a time series plot with prediction intervals is shown (event no. 2). Even though the accumulated relative deviation on the peaks in observation point I is positive, the model under predicts the peak in Fig. 12, as the 95% prediction fractile is less than the observed peak. With regards to the peak in observation point II, the observed peak fits nicely within the prediction interval. Despite the fact that the different key variables are kept within the prediction intervals (mean of all events) it is noticeable, by examining Fig. 12, that the model prediction is quite far from the observed in several points. This example shows the difficulties in applying a formal Bayesian statistical error model, since the bias is non-stationary and correlation in the error structures is present. It would indeed be complex to implement an error model including all these aspects.

Accepting simulations with  $L > 0.2$  and 0.1 also bracket both peaks, volumes and overflow durations, but clearly in wider prediction intervals than needed.



**Figure 10** Sensitivity plots, setup B2 – validation events. Solid distributions (posterior distributions) are the accepted simulations (5091/10,000) and dotted distributions are the non-accepted (4909/10,000).



**Figure 11** Bar plot of relative deviations corresponding to no. 3 in Table 4. Left side is related to the 5% fractiles and the right side to the 95% fractiles. The horizontal lines are the accumulated relative deviations for all events (nos. 1–6).

### Individual weighting of likelihoods

By calculating the relative deviations when each of the three likelihood measures are treated individually (e.g.  $L = 1 L_I \cdot 0 L_{II} \cdot 0 L_{III}$ ), it is possible to get an understanding of how the model performs in each of the three observation points. Moreover, it can also be studied how the model performs in the opposite observation points compared with the one on which the likelihoods are based. Using Table 4, no. 1 as a reference, the likelihood threshold of acceptability is changed so that 2045 simulations are accepted. The results are shown in Table 4 nos. 6–8.

It is remarkable that when using only  $L_I$  as a likelihood measure, observed peaks and volumes (in both observation point I and II) are bracketed by the prediction interval. However, it was expected that the model would be well-conditioned in observation point I, as the likelihoods ( $L_I$ ) are very large, but the fact that both peak and volume are bracketed in observation point II with only 2045 accepted simulations is unexpected. Similar results are not found in accepting simulations based solely on  $L_{II}$  and  $L_{III}$ . In fact accepting 2045 simulations solely based on  $L_{II}$  does not even bracket the peak value in observation point II, probably as a result of the interaction of an inadequate rainfall input with the global hydrological reduction factor used in the model.

### Weighting of likelihoods by runoff volumes

The final approach in testing weighting of likelihoods is based on a weighting in observation point I and II by the fraction of

the total observed runoff volume. The runoff volume in observation point I constitutes 62% of the total runoff volume and the corresponding value in observation point II is 38%. The combined likelihood function then yields:  $L = 1.28 L_I \cdot 0.78 L_{II} \cdot 1 L_{III}$  in order for the product of the weightings to be equal to 1. This approach is studied with the same thresholds of acceptability as in Section 'Equally weighted likelihoods', and results are shown in Table 4, nos. 9–12.

When comparing the approach with equal weighting of the likelihoods with this approach, it is clear that there is no advantage in weighting by the runoff volumes, as fewer simulations are accepted with the same likelihood threshold of acceptability.

### Discussion summary

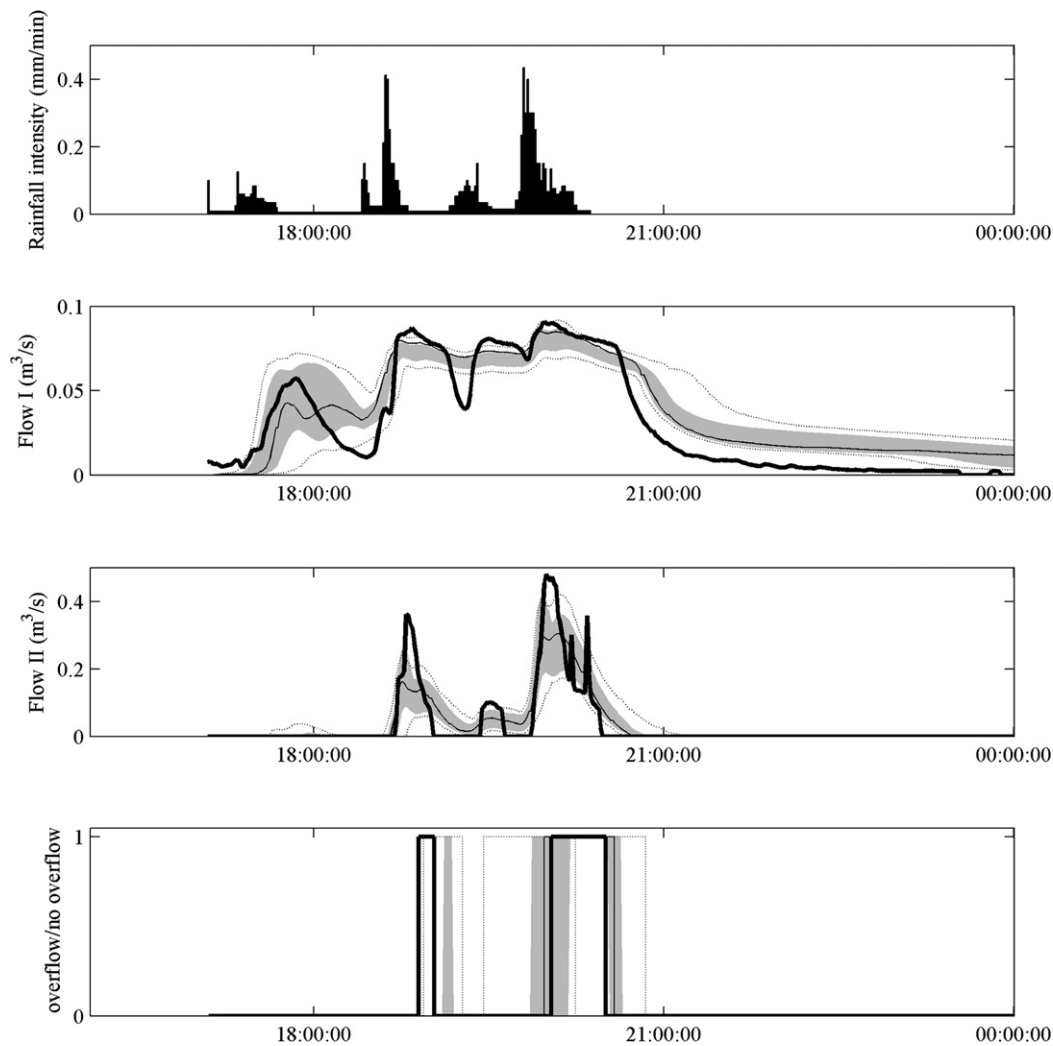
Different approaches of likelihood weighting and thresholds of acceptability are investigated. With equal weighting of the likelihoods it is possible on the average to fit observed peaks, volumes and overflow durations, within the model prediction intervals by accepting approximately 9000 or more out of the 20,000 simulations (corresponding to a combined likelihood larger than 0.3). It is obvious that the model performs the best in prediction of the flow in observation point I and also in prediction durations of overflow compared to the flow in observation point II, especially large peak value deviations within the individual are observed.

With the purpose of accepting fewer and better simulations in terms of model conditioning, it is not possible by introducing different likelihood weights to enhance this

**Table 4** Relative deviations between observed key variables and prediction intervals in the three observation points

No.	Criteria of acceptability	No. accepted	Observation point I				Observation point II				Observation point III			
			Relative deviations on peak	Relative deviations on volume	time in pred. interval	Relative deviations on peak	Relative deviations on volume	time in pred. interval	Relative deviations on volume	time in pred. interval	Relative deviations on peak	Relative deviations on volume	time in pred. interval	Relative deviations on peak
			$E_{\text{peak}}, 5\%, \text{I}$	$E_{\text{vol}}, 5\%, \text{I}$	$E_{\text{time}}, \text{I}$	$E_{\text{peak}}, 5\%, \text{II}$	$E_{\text{vol}}, 5\%, \text{II}$	$E_{\text{time}}, \text{II}$	$E_{\text{vol}}, 5\%, \text{III}$	$E_{\text{time}}, \text{III}$	$E_{\text{peak}}, 5\%$	$E_{\text{vol}}, 5\%$	$E_{\text{time}}, \text{III}$	$E_{\text{dur}}, 5\%$
1	$1 L_I \cdot 1 L_{II} \cdot 1 L_{III} > 0.5$	2045	-13.6	-7.0	28.5	-37.6	-12.2	20.0	-21.2	32.4	-21.2	-21.2	32.4	-21.2
2	$1 L_I \cdot 1 L_{II} \cdot 1 L_{III} > 0.4$	4472	-14.1	-7.4	30.7	-40.5	-15.4	37.1	-30.5	57.4	-30.5	-30.5	57.4	-30.5
3	$1 L_I \cdot 1 L_{II} \cdot 1 L_{III} > 0.3$	8780	-14.2	-8.7	35.3	-43.7	-23	58.2	-50.0	74.7	-50.0	-50.0	74.7	-50.0
4	$1 L_I \cdot 1 L_{II} \cdot 1 L_{III} > 0.2$	15,052	-15.2	-11.8	40.6	-51.4	-35.3	68.9	-57.1	88.1	-57.1	-57.1	88.1	-57.1
5	$1 L_I \cdot 1 L_{II} \cdot 1 L_{III} > 0.1$	19,088	-17.7	-18.7	42.2	-59.9	-49.6	76.2	-85.1	184.5	-85.1	-85.1	184.5	-85.1
6	$1 L_I \cdot 0 L_{II} \cdot 0 L_{III} > 0.938$	2045	-10.0	-7.8	36.6	-43.4	-29.4	53.2	-52.2	75	-52.2	-52.2	75	-52.2
7	$0 L_I \cdot 1 L_{II} \cdot 0 L_{III} > 0.714$	2045	-14.6	-11.4	33.0	-46.6	-34	23.8	-55.8	36.5	-55.8	-55.8	36.5	-55.8
8	$0 L_I \cdot 0 L_{II} \cdot 1 L_{III} > 0.840$	2045	-14.8	-7.4	30.0	-41.1	-11.4	18.8	-15.1	20.2	-15.1	-15.1	20.2	-15.1
9	$1.28 L_I \cdot 0.78 L_{II} \cdot 1 L_{III} > 0.5$	1432	-13.6	-6.9	28.0	-36.6	-11.7	15.4	-18.3	28.5	-18.3	-18.3	28.5	-18.3
10	$1.28 L_I \cdot 0.78 L_{II} \cdot 1 L_{III} > 0.4$	3770	-14.1	-7.4	30.1	-39.8	-14.9	33.3	-29.5	53.2	-29.5	-29.5	53.2	-29.5
11	$1.28 L_I \cdot 0.78 L_{II} \cdot 1 L_{III} > 0.3$	8040	-14.1	-8.2	34.4	-42.7	-20.7	55.3	-45.2	72.8	-45.2	-45.2	72.8	-45.2
12	$1.28 L_I \cdot 0.78 L_{II} \cdot 1 L_{III} > 0.2$	14,794	-15.2	-11.7	40.5	-51.1	-34.9	68.6	-56.4	87.8	-56.4	-56.4	87.8	-56.4

Bold script indicates that the value of the observed variable in question is outside the prediction interval, i.e. a positive relative deviation on the 5% prediction fractile or a negative relative deviation on the 95% fractile.



**Figure 12** Time series plots of event no. 2 accepting 8780/20,000 simulations ( $L > 0.3$ ). The bold black line is the observed time series, the thin black line is the simulation with the maximum likelihood, the grey area enclose the 5% and 95% prediction interval.

procedure, and with that accepting a higher likelihood threshold of acceptability. Therefore the uncertainty analysis in Sections 'Results' and 'Discussion' is performed with equal weighting and an acceptance criteria of  $L > 0.3$ .

All the likelihood measures used in this multi-criteria evaluation have been chosen in this empirical way. Clearly other choices of likelihood measure are possible but it seems that there are clear limitations as to how the MOUSE model can predict the critical values of peak flows, volumes and overflow durations in this catchment, either as a result of model structure limitations or because of input rainfall data limitations. If better models for peaks and volumes were available in the model space, then they are unlikely to have been rejected within the GLUE methodology as applied here. Thus further work needs to concentrate on improving the input data, or identifying limitations in the model representation of the drainage system.

## Conclusion

In the present paper it was investigated if the GLUE methodology could be used as an approach to uncertainty analysis

of the commercial urban drainage model MOUSE when conditioning on some observations in the Frejlev catchment. Based on the analysis the methodology has been shown to be very applicable, and it was possible to provide useful prediction bounds and identify limitations of the model.

One of the objects of the paper was to investigate different conceptual setups of the MOUSE model. It was investigated if the MOUSE model of Frejlev might be improved by applying an area weighted rainfall input from two gauges instead of the traditional approach, in which one gauge is considered to be representative for a whole catchment. This improvement was evident as both better fits and more behavioural simulations were observed. In addition to this it was investigated if the model might be improved by applying a more complex kinematic wave surface runoff sub model, compared to the simpler time-area surface runoff sub model. This was indeed also the case as better model predictions compared with the observations were detected in terms of a higher number of simulations exceeding the limits of acceptability. However, still less than 50% of the observations were bracketed by the model in this setup suggesting that non-aleatory errors in input data and model structure remain important. The choice of the conceptual



model setup showed insensitivity to the likelihood based on the duration of the combined sewer overflow.

Sporadically, large deviations between observed and modelled time series were detected, which probably were a result of model input uncertainties and to some extent model structural errors. GLUE, as applied here, did not take explicit account of uncertainties on the rainfall input, as there was not enough information available to parameterize rainfall uncertainties. However, the effects of input error are included in part in the event by event identification of the hydrological reduction factor which was found to vary significantly between events. The temporal dynamic errors associated with the rainfall are hence not considered. It could also be argued that the initial loss also should vary from event to event, to reflect an effect of antecedent conditions, but as this parameter is of minor importance regarding loading of the system (e.g. flooding and combined sewer overflow) this is neglected.

This therefore raises an issue about the prediction of future events which might have different relationships between input uncertainty and hydrological reduction factor. It will only be possible to address this using a forward uncertainty analysis, e.g. Thorndahl and Willems (2008) and Thorndahl (2008), as conditioned on what has been learned from the calibration events.

A sensitivity analysis was conducted in order to determine which parameters were the most important in the model setup. Without exceptions the hydrological reduction factor, determining the part of the impervious areas contributing to the runoff, was the most sensitive. Moreover, some sensitivity regarding the parameters governing the temporal variations of the surface runoff was shown. As for the parameters initial loss and dry weather flow as well as the Manning number in pipes and the headloss in manholes, a clear insensitivity to model output was demonstrated. As the model's response to the parameters applied in the GLUE analysis is quite small, one could argue that a simpler sensitivity analysis could be implemented instead of the GLUE concept. By only implementing the most important parameters the number of simulations could then be reduced remarkably.

Methodical aspects of the GLUE methodology were investigated in a discussion. As the choice of likelihood thresholds of acceptability are purely empirical, it was investigated how this limit influences the results, and in what range the thresholds should be in order for the model prediction intervals to be reliable. Moreover, different weightings of likelihoods in different observation points of the drainage system were investigated – concluding that an equal weighting was preferable.

The solid lines of Figs. 8 and 9 represent the posterior distributions of the three conceptual setups. These might be used as prior distributions in a forward uncertainty analysis of the drainage system loadings regarding long term statistics. Doing such an analysis would bring out important information on uncertainties in assessing return periods of combined sewer overflow as well as surcharge and flooding. Such an analysis is implemented in Thorndahl (2008). However, the derived posterior distributions might not represent a realistic interval, as the parameters to some extent compensates for other types of uncertainty, e.g. input or model structure. Therefore, the derived posterior should

only be applied in a similar conceptual setup of the same catchment.

## Acknowledgements

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## Paper VII

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### Stochastic long term modelling of a drainage system with estimation of return period uncertainty

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## **Stochastic long term modelling of a drainage system with estimation of return period uncertainty**

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### **ABSTRACT**

Long term prediction of maximum water levels and combined sewer overflow (CSO) in drainage systems are associated with large uncertainties. Especially on rainfall inputs, parameters, and assessment of return periods. This paper proposes a Monte Carlo based methodology for stochastic prediction of both maximum water levels as well as CSO volumes based on operations of the urban drainage model MOUSE (Lindberg and Joergensen 1986) in a single catchment case study. Results show quite a wide confidence interval of the model predictions especially on the large return periods. Traditionally, return periods of drainage system predictions are based on ranking, but this paper proposes a new methodology for the assessment of return periods. Based on statistics of characteristic rainfall parameters and correlation with drainage system predictions, it is possible to predict return periods more reliably, and with smaller confidence bands compared to the traditional methodology.

### **KEYWORDS**

Urban drainage modelling; long term simulation; extreme statistics; uncertainties; Monte Carlo simulation; flooding; combined sewer overflow; return period

### **INTRODUCTION**

The use of simulation models for hindcast prediction of flooding and combined sewer overflow occurrences in urban drainage systems has become an important tool for many consulting engineers and planners. Models, however, are often used with non-catchment specific parameters and are very rarely calibrated except for research use. The rainfall input (historical rain series recordings in a single point) cause model predictions to be uncertain, because the spatial rainfall variability is often ignored. Furthermore, in order to maintain design criteria, defined by the respective authorities, a certain safety is often implemented in parameter values so that predicted return periods are not exceeded within the specified limits.

Rainfall recordings during shorter periods of time entail great uncertainties in estimation of return periods. If a rain gauge has recorded for 10 years and the recordings are used as model input, it is not possible to determine whether the predicted maximum water level in a specific manhole should be assigned to a return period of 10 years, or maybe 50 or 100 years. Willems (2000) recommends that a maximum of 10 % of the total series length is applied as a statistically reliable return period. Other authors, e.g. Arnbjerg-Nielsen *et al.* (2002) use a maximum value of 25 % of total time series length. In urban drainage the Eurocodes of practice (EN 752-4. 1997) recommends a minimum return period of 10 years of flooding of combined sewers in residential areas. The design criterion is a return period of 2 years of

occurrence of surcharge (exceedance of pipe top level). A 100 year series is therefore necessary to estimate (with low uncertainty) whether a certain area will be flooded during a ten year period (using the definition of Willems (2000)). In this paper another approach is investigated. Based on deterministic simulation with a 60 year long rain series, a correlation between characteristic rainfall parameters and water levels as well as overflow volumes is defined. The return period of these are then assigned using a fitted return period model of the characteristic rainfall parameters which is based on statistics from a large number of Danish rain gauges.

Besides the return period uncertainties, parameter uncertainty is also included by random sampling and Monte Carlo simulation of the most important parameters. The uncertainties of the different parameters are propagated through the model in order to estimate the uncertainties on the model predictions. Therefore, this paper has two objectives: (1) to do a forward uncertainty analysis on long term simulations of a drainage system, in order to predict surcharge, flooding or combined sewer overflow with different return periods; and (2) to predict return periods in order to incorporate uncertainties using recorded rainfall time series as model input.

Several authors have investigated both input and parameter uncertainties in urban drainage modelling, e.g. Willems and Berlamont (1999), Arnbjerg-Nielsen and Harremoes (1996), Grum and Alderink (1999), Lei (1996), Thorndahl *et al.* (2006), Thorndahl and Willems (2008), Thorndahl *et al.* (2008), but most often modelling a number of either real or synthetic independent rainfall events. Thus, the extreme events and the return period uncertainty are neglected, although these events are the most interesting when considering the loading of the drainage system.

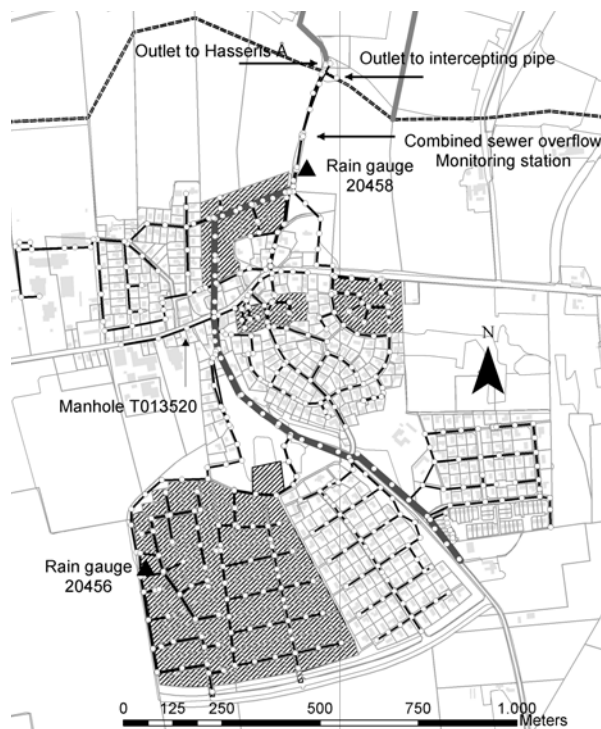
## **METHODOLOGY, LONG TERM SIMULATIONS**

Thorndahl *et al.* (2008) present an event based uncertainty analysis of a small urban catchment using the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley 1992). Based on corresponding rainfall-runoff measurements from the Frejlev catchment in Denmark (Figure 1), a stochastic calibration of nine independent events is carried out. The GLUE methodology includes a large number of Monte Carlo simulations with parameter values sampled from some selected prior distributions for each parameter. Propagated through a setup of a MOUSE model and weighted against observations using an empirical likelihood measure, a set of posterior distributions for each parameter is derived. In this paper these posterior parameter distributions are applied as a stochastic input to the same setup of the MOUSE model. It would be preferable to do a complete GLUE analysis using long term simulations, but the observation period is limited and therefore model conditioning on historical data is not possible for the whole period. Therefore, a forward uncertainty analysis, without conditioning on observations, is implemented. (Beven 2008). Furthermore, Thorndahl *et al.* (2008) introduce a comparison between two conceptual model setups. In the first, rainfall recordings from a single local rain gauge is used as model input, whereas in the second, an area averaged input from two local gauges is implemented. Using likelihoods as a measure of goodness of fit, it is shown that the model time series predictions are remarkably improved using the more complex rainfall input. However, the extremes, i.e. maximum water levels and combined sewer overflow volumes, does not seem to be significantly affected by the change in model input. Therefore, the model input to this setup will consist of one 20 year rain series recorded in the Svenstrup rain gauge, approx 4 km from the Frejlev catchment. This series includes 780 events with a rain depth larger than 1 mm. As shown on Figure 1,

two local gauges are installed within the catchment, but as these have a shorter running period (only 10 years) the dataset from these is not applied.

Even though recordings from only one rain gauge are applied, some of the uncertainty, related to the assumption of a homogenous rainfall distribution over the catchment, is implemented by the hydrological reduction factor. This factor determines the part of the impervious catchment area which contributes to the runoff. The reduction factor multiplied by the percentage of the impervious area corresponds to a general runoff coefficient. Based on more than 300 independent rainfall-runoff events in the Frejlev catchment, Thorndahl *et al.* (2006) and Thorndahl *et al.* (2008) have presented a remarkably small mean reduction factor of approx. 50 %. Furthermore, quite a large dispersion of the reduction factor is observed, which is probably due to the fact that spatially uniform rain is applied knowing that a spatial variation is present. The factor is therefore not only used to represent the part of impervious area that actually contributes to the runoff, but also as a measure of the spatial rain variability, however distributed homogenously over the catchment within one event. The other parameters applied in the model setup are presented in Table 1.

The uncertainty analysis is implemented using Direct Sampling Monte Carlo simulations in order to propagate the uncertainty on the parameters through the model. The simulation time of a long term model operation (780 events) of the Frejlev catchment is approx. 12 hours, but using a cluster of computers it has been possible to complete a total of 1000 simulations.



**Figure 1.** The Frejlev catchment and sewer system. The areas with hatching have a separate sewer system, the rest have a combined sewer. The main sewer line is the bold gray.

**Table 1.** Parameters applied in the MOUSE setup of the Frejlev catchment.  $N(\mu, \sigma)$  corresponds to a normal distribution with mean  $\mu$  and standard deviation  $\sigma$ .  $U(x_1, x_2)$  corresponds to a uniform distribution with lower and upper limit  $x_1$  and  $x_2$  respectively

Parameter	Distribution
Hyd. reduction. factor, $\varphi$ (-)	$N(0.49, 0.15)$
Initial loss, $i$ (mm)	$U(0, 0.8)$
Surf. concentration time, $t_c$ (min)	$U(0, 20)$
Dry Weather Flow, $DWF$ (l/(PE·day))	$U(90, 150)$
Manning number, $M$ (m <sup>1/3</sup> /s)	
Smooth concrete	$N(85, 5)$
Normal concrete	$N(75, 5)$
Rough concrete	$N(68, 5)$
Plastic	$N(80, 5)$
Head loss, $K_m$ (-)	
Round edged outlet	$U(0, 0.5)$
Sharp edged outlet	$U(0.25, 0.75)$

## METHODOLOGY, RETURN PERIOD ASSESSEMENT

The traditional way to assess return periods is by ranking e.g. event maximum water levels or CSO volumes. The event with the highest rank is assigned to the simulation period; the event with the second highest rank is assigned to half of the simulation period; the third half of the latter; and so forth. The return period of the events with the highest ranks is therefore quite uncertain. The ranking approach is applied in prediction of maximum water levels and CSO volumes in Figure 6 and 8, respectively.

The proposed approach to predict the return periods is also implemented a posteriori to the long term Monte Carlo simulations. The idea is to find correlations between some characteristic rainfall parameters and the model's prediction of maximum water levels and combined sewer overflow volumes. It is possible to assess return periods for the characteristic rainfall parameters quite accurately (and with confidence bands), thanks to a large Danish dataset. Knowing the correlation, it is possible to transform the return periods of the characteristic rain parameters to return periods of the model prediction. Using the Frejlev catchment Thorndahl and Willems (2008) showed a linear correlation between the rainfall event peak intensities and the maximum water level in manholes as well as a correlation between the rainfall event depth and duration and the CSO volumes. This is investigated further by doing a deterministic long term simulation based on the mean parameter values from Table 1 and a combined long Danish rain series from Odense. This series is not representative for the Frejlev catchment, it is only used due to its length of approx. 60 years (approx. 5000 rainfall events). Selected results are shown in Figure 2 and 3 for maximum water level and CSO volume relationships respectively.

Studying Figure 2 it is obvious that there is a linear relationship between the predicted water levels  $H_{max}$  and in this case the 10 minute averaged event peak intensity  $i_{p10}$ . The correlation depends on the parameters ( $\Theta$ ) from Table 1 so that:

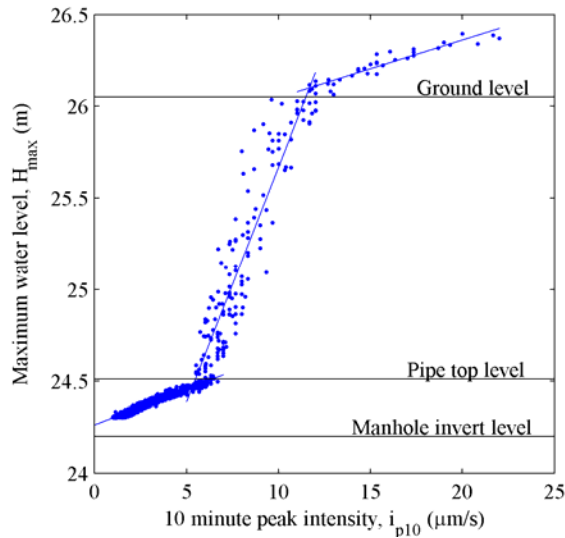
$$H_{max}(\Theta) \propto i_{p10} \quad (1)$$

With regards to the correlation between the CSO volume ( $V_{CSO}$ ) and the rainfall event depth ( $d$ ), it is obvious that interdependence with the rainfall duration ( $dur$ ) is present (Figure 3). The diagonal line corresponds to the maximum overflow volume:

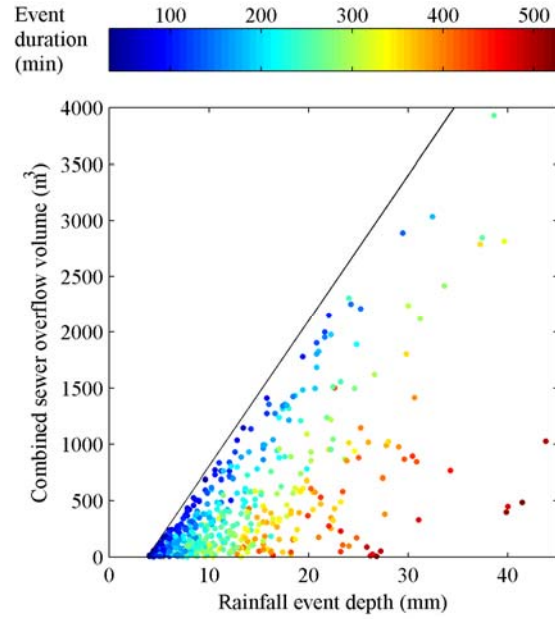
$$V_{CSO} = F_{imp} \cdot \varphi \cdot d + b = F_{imp} \cdot \varphi \cdot d - F_{imp} \cdot \varphi \cdot (\alpha \cdot dur + d_{min}) \quad (2)$$

$F_{imp}$  is the impervious area;  $\varphi$  is the hydrological reduction factor;  $b$  is ordinate cut-off value, which can be expressed as a function of the rainfall duration (not shown);  $\alpha$  is the correlation between the duration and the abscissa cut-off value; and  $d_{min}$  is the minimum cut-off value corresponding to the minimum rainfall depth which will cause overflow. Therefore the overflow volume can be expressed as a function of the rainfall depth and duration:

$$V_{CSO}(\Theta, dur) \propto d \quad (3)$$



**Figure 2.** Linear relationships between the maximum event water level and the 10 minute peak intensity in manhole T013520.



**Figure 3.** Relationship between the rainfall event depth and the overflow volume. The colour graduation indicates the rainfall event duration.

Using the derived correlations, the return periods of maximum water levels are estimated using the return period of the peak intensities averaged over a period of time corresponding to the transportation time in the sewer system. Upstream in the sewer system this corresponds to the 10 min. averaged peak intensity, further downstream the 20 and 30 min. averaged peak intensities are applied. Correspondingly, the return periods of the CSO volumes are estimated using the return period of the rainfall event depth.

In Spildevandskomiteen (2006) and Madsen and Arnbjerg-Nielsen (2006) 66 Danish rain gauges have been used to estimate key rainfall parameters with return period uncertainty based on measurements from 1979 – 2005. The dataset from these gauges is statistically approximated to a partial duration series model (Madsen and Rosbjerg 1997a; Madsen and Rosbjerg 1997b; Mikkelsen *et al.* 1998). Applying a generalised Pareto distribution, a fit of the return periods is estimated (Spildevandskomiteen 2006):

$$\hat{z}_T = z_0 + \hat{\mu} \frac{1 + \hat{\kappa}}{\hat{\kappa}} \left( 1 - \frac{1}{\hat{\lambda} \cdot T} \right)^{\hat{\kappa}} \quad (4)$$

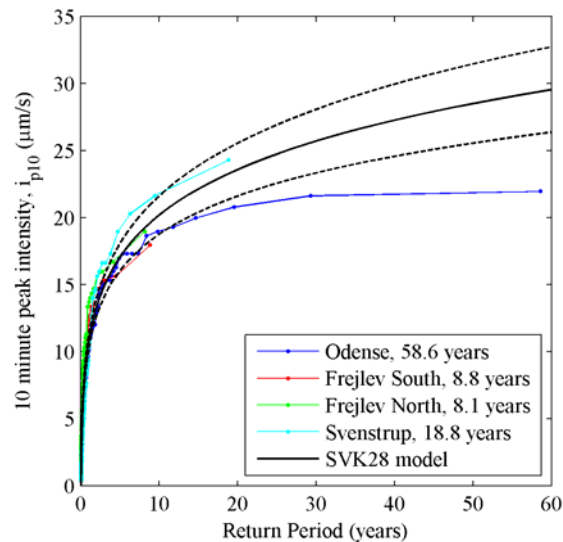
$z_T$  is the value corresponding to the return period  $T$ , e.g. 10 minute peak intensity or rainfall event depth,  $z_0$  is a cutoff level,  $\mu$  is the mean of the exceedings of  $z_0$ ,  $\kappa$  is a shape parameter and the number of yearly exceedings,  $\lambda$  is estimated by (Spildevandskomiteen 2006):

$$\hat{\lambda} = \hat{\beta}_0 + \hat{\beta}_1 \cdot YMP \quad (5)$$

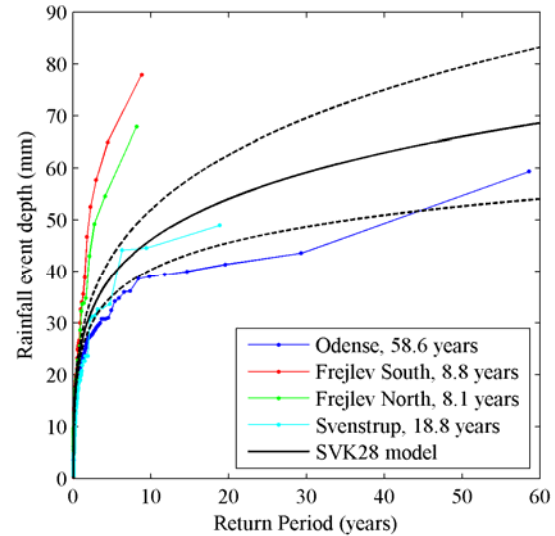
$\beta_0$  and  $\beta_1$  are linear regression parameters and  $YMP$  is the regional accumulated yearly precipitation. The variance of the number of yearly exceedings is based on:

$$\text{var}(\hat{\lambda}) = \text{var}(\hat{\beta}_0) + 2 \cdot YMP \cdot \text{cov}(\hat{\beta}_0, \hat{\beta}_1) + YMP^2 \cdot \text{var}(\hat{\beta}_1) + \hat{\sigma}_\delta^2 \quad (6)$$





**Figure 4.** Return periods for the 10 minute maximum rainfall intensity, using reel measured data and the Pareto model



**Figure 5.** Return periods for the rainfall event depth, using reel measured data and the Pareto model

The statistics presented in Spildevandskomiteen (2006) have resulted in a division of the Danish rainfall statistics in two regional zones, one for the Western part of Denmark and one for the Eastern part. Using the accumulated yearly precipitation a local estimate of the return period uncertainty can be calculated. Shown here are observed local values of the 10 minute peak intensity (Figure 4) and the rainfall event depth (Figure 5) along with the Pareto model. It is obvious in both figures that the return periods estimated in the local series do not fit completely within the 95 % confidence interval of the Pareto model. This is due to the relatively short measuring period. However, in the area of 10 % of the series length the data fits quite well within the confidence bands of the Pareto model using the recommendations of Willems (2000).

Based on the above, the return periods predicted with the correlation between the peak intensity and the maximum water level correlation ( $i_p-H_{max}$ -correlation) are assessed as presented in this example. If a peak intensity is observed in a specific recorded rainfall event, the mean return period and the 95 % confidence intervals are estimated based on the Pareto model in Figure 4. The return period of the maximum water level for this specific event is then sampled using a triangular distribution applying the mean estimated return period and the variances. For each simulation of the maximum water level a total number of 100 return periods are sampled. As 780 events are included in the Svenstrup rain series and 1000 Monte Carlo runs are simulated, this yields a total of 78 million events with different return periods.

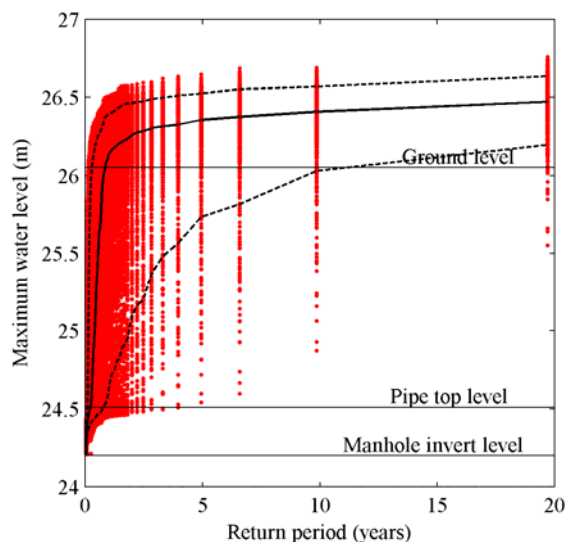
The return periods of overflow volumes based on the depth-duration-CSO volume ( $d-dur-V_{CSO}$ ) correlation are estimated by the simulated overflow volume, the hydrological reduction factor, and the observed rainfall event duration. Using eq. 2, a rainfall depth is estimated and the return period for this specific depth is given by the Pareto model of Figure 5. The return periods of the CSO volumes are also sampled with triangular distributions.

## RESULTS

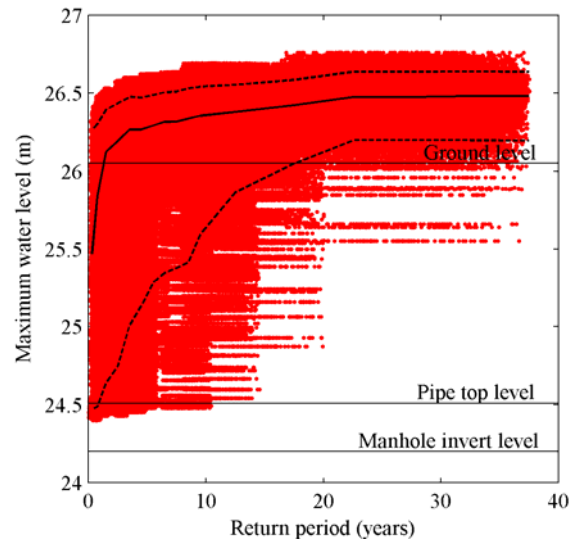
The traditional ranking methodology used to estimate return periods of water levels is presented in Figure 6 for the most critical manhole in the system (Manhole T013520, Figure

1). It is obvious, doing 1000 Monte Carlo simulations, that the dispersion of the predicted water levels for this manhole is quite large. This is primarily due to the standard deviation applied on the hydrological reduction factor, as this is by far the most crucial parameter (Thorndahl *et al.* 2008). The dispersion is especially large in prediction of water levels between the pipe top and the ground level, which is evident as the storage volume in this area is very small, and small changes in rainfall intensity or depth involves a great change in the water level. In Figure 7 return periods predicted by the  $i_p$ - $H_{max}$ -correlation methodology are presented. Comparing the two figures, it is clear that the return periods are equal at low values. However, the high return periods of Figure 6 are more uncertain, as the maximum return period is assessed equally to the time series length. As the  $i_p$ - $H_{max}$ -correlation, using the Pareto model, has no upper limit, the predicted water levels are assigned larger return periods. In order to compare the probability of flooding of the manhole, the predicted water levels exceeding ground level are selected and the cumulative distribution function of the return periods of these events are derived, Figure 10. Again, it is evident that the difference between the two approaches is large when the return period is large, however quite identical low return periods are present. As an example the probability of flooding this manhole every year is 62 % using the return period ranking methodology and 47 % using the  $i_p$ - $H_{max}$ -correlation and Pareto model. The manhole is the most critical in the system, with very frequent flooding, and actually the drainage system was recently redesigned, so flooding problems no longer occur.

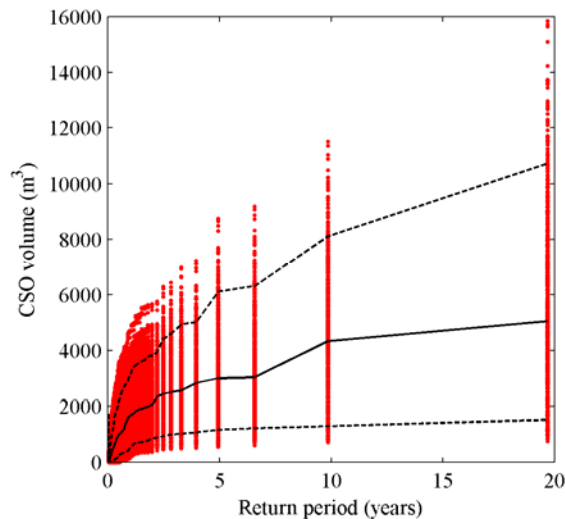
With regards to the prediction of CSO volumes (Figure 8 and 9) the tendency is the same as in prediction of water levels, i.e. the return periods using the ranking methodology are quite uncertain, but the results are similar on the low return periods. The new proposed methodology reduces the confidence interval on the large return periods. For example, the 20 year return period has a 95 % confidence interval corresponding to 3500 m<sup>3</sup> and 7500 m<sup>3</sup> applying the proposed methodology, however the ranking methodology show a 95 % confidence interval of 1500 m<sup>3</sup> and 10500 m<sup>3</sup>. So in this case the interval is reduced to approx. one third, applying the new approach.



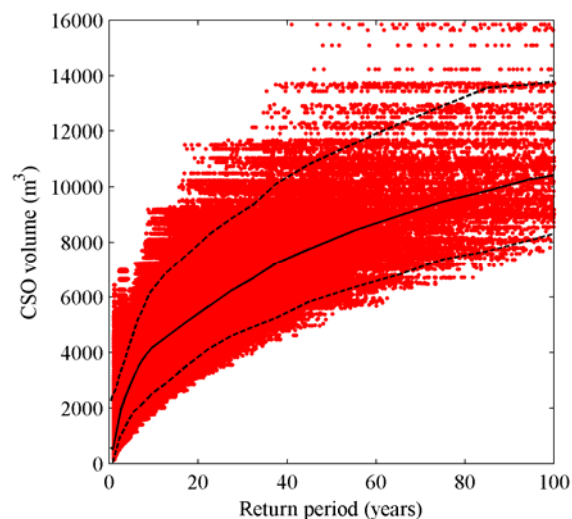
**Figure 6.** Return periods by ranking of maximum water levels, Manhole T013520. The solid line is the median and the dotted are the 95% confidence interval.



**Figure 7.** Return periods by intensity-water level correlation, Manhole T013520. The solid line is the median and the dotted are the 95% confidence interval.



**Figure 8.** CSO volumes and return periods by ranking. The solid line is the median and the dotted are the 95% confidence interval.



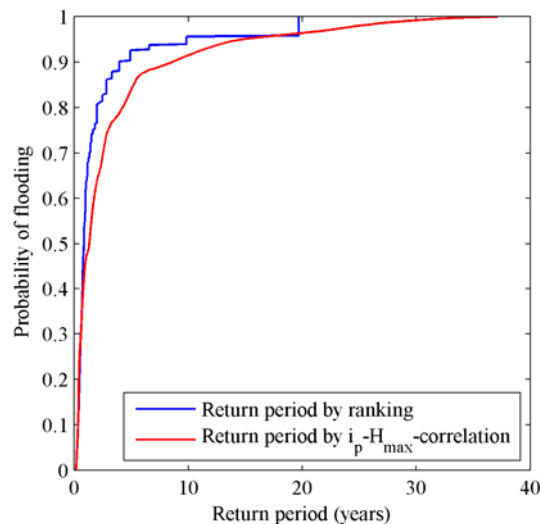
**Figure 9.** CSO volumes and return periods by  $i_p$ - $H_{max}$ -correlation. The solid line is the median and the dotted are the 95% confidence interval.

Figure 11 presents the maximum water levels corresponding to the 2 year return period as a profile view of the main sewer line. Both methods show that the median and the mean (not shown) maximum water level exceeds the pipe top level in some of the pipe sections, so that the manholes are surcharged. This causes an exceedance of the design criteria recommended in the Eurocodes of practice (EN 752-4, 1997). The two methodologies perform equally in prediction the 2 year return period. It would be preferable to show the 10 year return period as well. This, however, has only occurred in 2 of the 39 pipe sections shown in Figure 11 (applying the  $i_p$ - $H_{max}$ -correlation methodology). Therefore, it is concluded that the Eurocodes are kept with regards to the criteria of no flooding within a return period of 10 years, when the proposed methodology is applied. However, when applying the ranking methodology the water level corresponding to the 10 year return period is exceeded several times. It is therefore concluded that the large return periods are over-estimated when applying the ranking methodology.

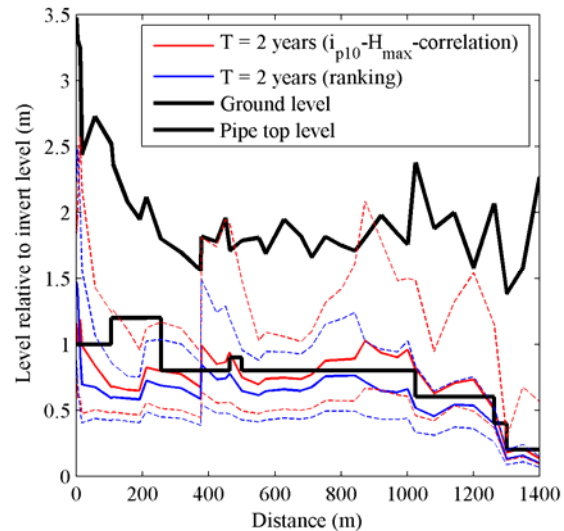
## CONCLUSION

This paper has presented a stochastic urban drainage model in which uncertainties of different parameters are sampled by performing Monte Carlo simulations. The parameter distributions are based on posterior distributions from a previous investigation (Thorndahl *et al.* 2008) in which a conditioning of the model is carried out using the GLUE methodology. A homogeneous spatial rainfall distribution over the catchment in every event is assumed, however the spatial rainfall variability is assessed using a wide sampling interval of the hydrological reduction factor which varies from event to event. It is clear that this might affect the predicted dynamics (i.e. the temporal flow variations) of the system to some extent. However, as this paper only concerns the extreme event statistics, it is the author's conviction that omission of the spatial rainfall variation is valid - especially as the catchment in question is rather small.

In order to investigate if an adequate number of Monte Carlo simulations is executed, the model prediction statistics are completed using both 500 and 1000 simulations, however with no significant difference of the confidence interval. This concludes that enough simulations are executed.



**Figure 10** Probability of flooding in manhole T013520



**Figure 11** Median max. water level and 95 % confidence bands for a return period of 2 years. The profile corresponds to the thick gray main sewer line on Figure 1.

The predicted maximum water levels and CSO volumes cover quite a wide confidence band, particularly on the large return periods. This confidence band might be narrowed if a conditioning on some observations is implemented, e.g. using the GLUE methodology. However, this would only affect the prediction of maximum water levels and CSO volumes, and not the uncertainty associated with the return periods, unless continuous observations in the drainage system are available for the whole simulation period. Consequently, an approach to handle uncertainties on the return periods is also presented in the paper. By investigating the correlation between characteristic rainfall parameters and maximum water levels as well as overflow volumes, a model for assessing the return periods is assembled. This is based on 26 years of statistics on several Danish rain gauges (Spildevandskomiteen 2006). Using the return periods of the characteristic rainfall parameters it is possible to assess return periods of maximum water levels and CSO volumes applying linear correlations. Comparing the traditional way of assessing return periods by ranking and the proposed model a good agreement between the two approaches is shown where the return periods are low. However, on the large return periods the proposed correlation model shows more realistic results (and smaller confidence bands), as the statistical basis of assessing return periods is much larger. As the relationship between the rainfall parameters and the drainage system predictions are based on simple linear correlations, obviously some of the dispersion between the two is neglected, which might introduce a small uncertainty. Furthermore, as the approach is only tested on this small catchment which performs quite linearly, it is not possible to conclude whether the approach will work on a larger and more branched drainage system. Finally, it is not tested whether the predicted return periods actually correspond to actual occurrences in the drainage system. Preferably, further investigations will show that this is the case.

The concept of identity between the return periods of characteristic rainfall parameters and prediction of water levels is also proposed in the scientific literature, e.g. using the Chicago design storm (Kiefer and Chu 1957). This, however, includes a number of disadvantages as some of the rainfall dynamics are neglected (due to synthetic storms) and the fact that it is not possible to estimate CSO volumes using this method. The proposed methodology therefore

presents an alternative to return period prediction of maximum water levels and CSO-volumes on small simple catchments.

## ACKNOWLEDGEMENT

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